Human Capital Movement: Effects on Research Productivity in the Pharmaceutical Industry

by

Michael Douglass Rees

B.S. Mechanical Engineering
B.A. Political Science
University of Pittsburgh (1997)

Submitted to the Department of Mechanical Engineering
And the Technology and Policy Program in Partial Fulfillment of the Requirements for the Degrees of

Master of Science in Mechanical Engineering

And

Master of Science in Technology and Policy

At the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

JUNE 1999

Signature of Author
.....
Technology and Policy Program
Department of Mechanical Engineering
May 21, 1999

Certified by
.....
Dr. Rebecca M. Henderson
Thesis Supervisor
Professor of Management

Certified by
.....
Dr. Anna C. Thornton
Mechanical Engineering Department Reader
Professor of Mechanical Engineering

Accepted by
.....
Dr. Richard de Neufville
Chairman, Technology and Policy Program

Accepted by
.....
Dr. Ain Sonin
Chairman, Departmental Committee on Graduate Studies

TABLE OF CONTENTS

Human Capital Movement: Effects on Research Productivity in the Pharmaceutical Industry

By

Michael Douglass Rees

Submitted to the Department of Mechanical Engineering
And the Technology and Policy Program in Partial Fulfillment of the
Requirements for the Degrees of

Master of Science in Mechanical Engineering
&
Master of Science in Technology and Policy

ABSTRACT

Firms in high-tech industries rely heavily on their ability to innovate. Firms in the areas of biotechnology, pharmaceuticals, semiconductors, and microelectronics depend on the productivity of their in-house research facilities to support their product pipeline. Understandably, the productivity of employee working in the research laboratories of these firms is of considerable interest to managers, recruiters, and investors. Because of its importance, I explore the ways in which factors associated with human capital quality affect the research productivity of firms in the pharmaceutical industry.

In this thesis I present an assessment of the aggregate human capital quality embodied by the top scientists at the major firms in the pharmaceutical industry. Then I examine whether this quantified level of human capital relates to different levels of research productivity. Secondly, I observe the amount of human capital movement in the pharmaceutical industry and compare it to other high-tech, information intensive industries. The relative amount of human capital movement for the various industries provides insight into structural and personal aspects of the labor market for talented employees in high-tech industries. The final phase of this study attempts to quantify the movement of human capital into, out of, and among firms in the pharmaceutical industry, and attempts to predict how these movements may affect productivity.

I find that human capital quality is an excellent predictor of research productivity in the pharmaceutical industry. Also, I show that measures of centrality in the network of human capital movements are positively correlated with research productivity. Implications of these findings are far-reaching, as tremendous effort is presently spent trying to identify additional drivers of productivity. Policy in the areas of corporate recruitment, employee development, and organizational structure all benefit by understanding the link between human capital quality and productivity.

Thesis Advisor: Dr. Rebecca Henderson
Mechanical Engineering Reader: Dr. Anna Thornton
Technology & Policy Advisor: Dr. Richard Tabors

ACKNOWLEDGEMENTS

I'd like to thank Dr. Rebecca Henderson, for giving me the opportunity to pursue work in this field. I don't think you could have envisioned the trouble I was to cause you, that day eighteen months ago when I walked into you office. The work contained in this thesis is a far cry from the vibrational analysis I was to perform on a Ford Taurus drivetrain. It's been a great journey, and I've learned much along the way. Because of your schedule, your time is very precious. But more precious, to me, are the insights you've given me, as well as the confidence you've had in me. Thank you.

I'd also like to thank Professor Anna Thornton and Professor Richard de Neufville for serving as thesis readers in their respective academic departments.

To Kary Hisrich, for graciously accepting my work schedule and often stressful nature over the past few months. I've enjoyed every minute we've spent together.

In the acknowledgements section of many publications, you often find the phrase "This work would not have been possible without the help of _____." In my case, this sentiment holds doubly true. Not only have Kary Hisrich, Marc Ingoglia, Amy Kline, and John Cochran provided support through various social channels, but they also collected much of the data. Truly, this thesis would not even exist if it were not for the tireless data gathering of my friends.

But most of all, I'd like to thank my mother, my father, and my brother for being such a positive part of my life, past and present. There's not much more to say. Thank you for always being there, I love you.

I. Introduction

While companies in some sectors are able to survive or even prosper by improving incrementally on yesterday's business activity, firms in the hyper-competitive high-tech industries do not have that luxury. To stay competitive and avoid extinction, these firms must innovate continuously and provide new products or technology to consumers. Identifying the drivers of innovation is a tenuous task, to say the least, as managers, scholars and investors all seek to pinpoint the fundamental ingredients and proportions that combine to produce a highly innovative, productive firm.

For these firms, the ability to innovate feeds directly into their prosperity and longevity. The revenues, employees, and products of tomorrow are dependent upon the innovation of today. This requirement for continuous innovation has caused some industries to become dependent upon research conducted inside of the firm. No longer can firms wait for academic or government institutions to act as their source of advancements in basic research.

The economics and management literature is heavily populated with studies of the optimal levels of ***investment spending***. Just a few examples include numerous studies that link productivity and research spending in the electronics industry (Ernst [1998]), biotechnology industry (Arora and Gambardella [1994]) and U.S. consumer product industry (Samuel [1998]). Also existing is a vast literature detailing ***organizational drivers*** of productivity in

high-tech industries (Valente [1989], Gambardella [1992], Henderson and Cockburn [1994, 1998], Bulger [1994-1995], etc. to name just a few).

One factor affecting performance that has been relatively unexamined, however, is ***the quality of the employee***. The quality of human capital employed by an institution could be just as important in affecting performance as capital/research spending or organizational structure. Not only is the topic of industry-wide human capital quality relatively uncommon, but also studies of firm-level human capital quality are rather scarce. This study contributes to the literature that focuses on the subject of human capital and its link to productivity.

In this thesis I present an assessment of the aggregate human capital quality embodied by the top scientists at the major firms in the pharmaceutical industry. Then I examine whether this quantified level of human capital relates to different levels of research productivity. Secondly, I observe the amount of human capital movement in the pharmaceutical industry and compare it to other high-tech, information intensive industries. The relative amount of human capital movement for the various industries provides insight into structural and personal aspects of the labor market for talented employees in high-tech industries. The final phase of this study attempts to quantify the movement of human capital into, out of, and among firms in the pharmaceutical industry, and attempts to predict how these movements may affect productivity.

Background/Prior Art: With so much attention paid to plethora of ways in which a manager can organize groups of employees in hopes of squeezing the last bit of productivity from them, it seems odd that few have attempted to address a much more fundamental question: Does the quality of the employee differ significantly across firms, and if so, does a higher level of human capital translate to a higher level of performance?

Quality of Human Capital: Jaehn [1985] presented numerous means of assessing the organization-wide level of employee quality. With the ultimate goal of explaining drivers of manager productivity, Tharenou [1997] compares the quality of human capital for various Australian industries. The findings of that study downplay the importance of aggregate human capital level and point to individual *leadership traits* (ambition, motivation to manage, general cognitive ability, etc.) as the key drivers. Bulger [1995-1996] maintains that organizational structure is the major determinant of productivity, and that the quality of the employee is merely a first-order contributor. Patibandla and Chandra [1998] survey the Canadian textile industry, finding rather large discrepancies in the quality of the employee of the major corporations; however, they find the structuring of personal incentives to be a much better predictor of performance than is the quality of human capital.

Importance of Human Capital: The importance of human capital is a topic fit for numerous forums. On the level of macroeconomics, even, Hayami and Ogasawara [1999] cite the ability of the US economy to shift its bias away from physical capital appreciation to human capital appreciation as a predominant driver of the widening gap in total factor productivity between the US and Japan in the 1990's. Focusing on firm-level human capital

issues provides insight into these productivity drivers that can not be found in macro-level calculations. Within the context of the pharmaceutical industry, however, Zucker and Darby [1995] examine the highest level of human capital at universities and firms conducting research in the area of biotechnology. They find that the locus of innovation for much of the industry is derived from the work of the scientific elite. I ask why human capital quality would seem more important in information intensive, innovation driven industries. With a great body of the literature suggesting human capital quality's rather insignificant contribution to the overall performance of organization, I sought to answer the question as to whether this observation held true for information-intensive industries, or if the predictions of Zucker and Darby [1994] and Zucker, Darby, and Brewer [1998] hold true for pharmaceuticals as well as biotechnology.

Human Capital Movement: On the subject of human capital movement, there exists a rich literature describing the boundaries that impede the free flow of labor in an economic sense. Arthur [1994] with DeFillippi [1995] and with Claman and Adams [1995] describes an evolving model of the labor market in high-tech, information intensive industries. Their work details some of the personal and institutional factors that restrict the perfect flow of human capital as one of the primary economic factor inputs. Drawing upon the work of numerous others, they describe the development of a nearly efficient labor market that has been (or, in some cases, is being) created for high-tech industries, such as pharmaceuticals. The *Boundaryless Culture*, as they have called it, is marked by high-levels of human capital movement caused by structural shifts and employee psychological changes. I examine

whether the levels of human capital movement observed/predicted by Arthur, et al are consistent with those I find for elite pharmaceutical scientists.

Human Capital Movement in the Pharmaceutical Industry: Gunz's [1999] and Gunz and Jalland's [1990, 1996] studies of the aggregate level of human capital movement in the Canadian Biotechnology Industry found an extremely low rate of inter-firm employee transfers. While the study focused on upper management positions, (where employees would be expected to have a larger portion of their personal capital tied to the firm,) it serves as a benchmark level to which the pharmaceutical industry can be compared. At the other end of the spectrum, Rogers' [1984] and Sexenian's [1990, 1991, 1992, 1994a, 1994b] numerous descriptions of the human capital movement exhibited for skilled professional of the high-tech companies in Silicon Valley highlight the epitome of boundarylessness and efficient labor market activity. I use a comparison of observed rates of human capital movement for these various industries as a springboard to a discussion of some of the structural labor market [in]efficiencies and how they affect research productivity.

Firm-level Human Capital Movement: On the topic of firm-level human capital movement, Angel [1989] conducted a study of the rates found for engineers in the semiconductor industry. He suggests that the very high level of human capital movement serves as an excellent conduit for the flow of industry-wide and firm-specific information. Spillovers derived from the flow of information via organizational network or collaborative efforts have been shown to be significant drivers of research productivity in the pharmaceutical industry (Henderson and Cockburn [1993], Acs and Audretsch [1988,

1993], Jaffe [1989], Jaffe, Trajtenberg, and Henderson [1993], Acs, Audretsch and Feldman [1994], Griliches [1992]). I ask whether the information flow inherent in human capital movement drives research productivity in a similar fashion. Through this study I hope to identify inter-firm personnel movements as an additional vehicle for productivity enhancement, brought about by increased information flow.

Human Capital Movement – Channel for Tacit Knowledge: Zucker, Darby and Armstrong [1994] explore the topic of intellectual capital: "a specialized body of knowledge that enables the individual to earn supernormal returns on his/her knowledge." They identify the spillover of this intellectual capital as a driving force in the creation and explosive growth of the biotechnology industry. They suggest that tacit knowledge, the intangible knowledge possessed by the elite, is a valuable commodity in an innovation-dependent industry. I, therefore, hypothesize that a star scientist embodies extremely high levels of intellectual capital and tacit knowledge, and that an inter-firm movement of these scientists represents the extreme case of knowledge spillover. Important policy implications arise in the case where higher levels of human capital movement translate to increased productivity. Corporate resource management policy, in the areas of hiring and retention, becomes increasingly important in the world described by Zucker, Darby and Armstrong.

The Human Capital Movement Network: The social and organizational network as factors influencing research productivity and output are topics covered extensively in the literature. Burt's heavily-cited work on the topic of social capital and structural holes [1997] describes how the structure of the social network can vary across industries, and that

productivity tends to be higher in those industries that are capable of strengthening inter-firm network ties. Valente and Foreman [1998] construct a measurement of the connectedness of the nodes of a social network and discuss ways in which this measure of network centrality may link to certain output variables. I explore whether a firm's position in the network of inter-firm human capital movement is correlated with research productivity.

Why the Pharmaceutical Industry? As a means of studying links between human capital and productivity, an industry that relied heavily upon a constant stream of innovation seemed to be best suited. For industries such as pharmaceuticals, biotechnology, semiconductors, and microelectronics, the competitive landscape and knowledge base are very dynamic. The complexity of information is ever increasing, and state-of-the-art methods, techniques, and technologies can have very short lifetimes, thus magnifying the importance of highly trained employees.

Gambardella's [1992] numerous case studies of firms in the pharmaceutical industry show that conducting basic research is a survival requirement, and that the ability of a firm to capitalize on the vast public knowledge is dependent upon the level of in-house research being conducted. Though the literature is not unified in the measurement of actual returns to basic research conducted inside of the firms (Jones and Williams [1995], and Stephan [1996]), few would argue against the hypothesis that an elevated ability to conduct basic research inside of the firm, and assimilate information from the outside, correlates positively with drug discovery. The pharmaceutical industry's importance in the business landscape

has increased greatly over the past decades. Phenomenal growth levels in the areas of sales, earnings, market capitalization, research spending and the number of employees has increased competition in the industry and heightened the importance of a talented workforce. With such an information-intensive industry amidst such high patterns of growth, an understanding of the relationship between human capital and productivity seems fitting.

Research Methodology: The analysis is based heavily on publication data for each of the scientists in the sample. A comprehensive publication record will be developed for each scientist associated with the firms in the sample. These records will track the employment and publication frequency for each scientist. Authors with consistently high levels of publication will be identified as scientific elite, and followed for the remainder of their careers. By identifying the origin of publication for each author, I will be able to track a scientist's movement throughout the pharmaceutical industry. From these data I will construct various firm-level variables that capture different aspects of the flow of elite scientists between the sample pharmaceutical firms.

A firm's research productivity will be proxied by the number of *important patents* it successfully obtains. As the primary objective of the basic research conducted at pharmaceutical firms is aimed at identifying new, novel, or alternative drug candidates or technologies, a measure of the rate at which a firm acquires patents adequately captures the aggregate level of research productivity. As a means of mitigating problems that arise because different firms vary in their dedication to filing for patents, to qualify as an

important patent, protection must have been sought in two of the three major markets (Japan, Europe, or the U.S.).

Human Capital scores will be given to each of the scientists on the basis of the academic reputation of the college or university program from which a scientist received a Ph.D. While not foolproof, the use of graduate program reputation as a measure of the intellectual ability of its graduates is common in many areas of social science research.

Chapter II presents a full description of the global author database that was used as the primary source of data. It also describes the analysis techniques that I used to identify STAR authors. Chapter III contains descriptive statistics for STAR authors and a discussion of the impact of human capital quality, as measured by the number of STAR scientists, on research productivity. Chapter IV describes an alternative means of measuring the human capital quality of the STAR scientists, and whether it serves as a better predictor of research productivity. Chapter V quantifies the aggregate level of human capital movement for the pharmaceutical industry as an entity, and includes a discussion of some of the ramifications of labor market structure for innovation-driven, high-tech industries. Chapter VI addresses firm-level human capital movement statistics and the virtues of a *central* position in the human capital movement network. Chapter VII contains concluding remarks.

II. Methods and Data – Global Author Database

For a study concerning possible drivers of the productivity of basic research centers at major pharmaceutical firms, one needs a means of quantifying the *amount* of basic research being conducted. Publication data provides a rather suitable means of measuring the amount of basic research done by a firm. While the dedication to publication varies significantly across firms in the sample, nonetheless, as a publicly available source of data, publication counts are very useful. Research and development spending data that are released to the public are relatively ambiguous, as it is often very difficult to separate actual basic research spending from the costly development phases of drug development. The allocation of R&D dollars between each of the two phases in the drug discovery chain also varies significantly across the sample firms, and therefore R&D spending statistics are not particularly useful as a broad measure of the amount of basic research being conducted inside of the pharmaceutical firm.

The following analysis utilized a database of publication records for scientists related to the pharmaceutical industry. The time-period over which the data was taken was 1980-1994. As a means of providing continuity, the 20 pharmaceutical firms studied by Cockburn and Henderson [1998] were used to define the universe of pharmaceutical firms. Henderson and Cockburn chose these firms as a representative sample of the major research-oriented pharmaceutical firms. While this sample in no way comprises the entire body of research activity conducted by pharmaceutical firms world-wide, it does account for a large portion

of the small-molecule pharmaceutical research conducted by US pharmaceutical firms, as well as a sample of the highly regarded research firms in Europe and Japan. The firms included in the study are listed in Exhibit 1.

The question as to whether the quality of human capital influences the productivity of the basic research being conducted at the sample pharmaceutical firms is difficult to grasp on two dimensions. First, a means of identifying or measuring the quality of human capital must be found. This presents numerous problems of endogeneity. If the measurement is made along a dimension that could be interpreted as a result of productivity, then a cause-effect problem arises. The measure of human capital quality was initially made from publication data because these data represent a quantifiable contribution to the research community. The productivity proxy was chosen to be patent data (as described by Henderson and Cockburn [1994]). The tension between knowledge-expanding publication and intellectual property protection draws a nice distinction between the measure of human capital (from publication data) and the measure of productivity (patent data). From the standpoint of economics, discovery information as a factor-input is often viewed as freely available. Economic gains are realized by those who create/discover information and transform it to the point where it can be sold for a profit. In the area of drug discovery, this economic phenomenon is embodied by the acquisition of patents that formalize advancements in "information" towards the point of commercial viability. The output of *important patents* has been used previously as a predictive metric of pharmaceutical research productivity, (more extensive definition and further description to follow, see also,

Henderson and Cockburn [1994,1998]). For the firms in the sample, average patent productivity data are presented graphically in Exhibit 2.

Publication data were gathered from all of the journals indexed in the Institute for Scientific Information's Science Citation Index. The address field in the Science Citation Index was queried for the firm name (and all apparent permutations and variations) for each of the 20 firms in the sample. The results represented the global set of publications originating from, or associated with, each firm. It should be noted that there exists a high degree of coauthorship for these publications. For the firms in the sample, the average paper contained 4.4 coauthors and 1.86 addresses. Further coauthorship statistics and analysis can be found in Cockburn and Henderson [1998].

As a means of linking individual authors with their employer, the global set for each firm was then searched for papers with only one address. This enabled the generation of a list of authors from each firm and eliminated those coauthors from outside of the firm. One of the primary shortcomings of this process is that it fails to identify those authors employed by a firm who never publish as an individual author. Because the following work will focus on only the most prolific scientists, it is believed that problems associated with this shortcoming are mitigated. Once the authors for a given firm had been identified, the global publication set was then searched to determine the total number of papers published by that author in each year of the 15 year time period (1980-1995).

This process resulted in the identification of 36314 authors and a total publication count of 191288. Exhibit 3 contains the breakdown of the total number of authors by firm and by total number of papers published over the 15-year period. Noticeably, a considerable number (12265) of the authors publish only one paper, representing about one-third of the total number of authors. Furthermore, three-fourths of all authors publish five or fewer papers. This goes to show the high-degree to which the data are skewed towards lower number of publications. (See histogram, Exhibit 4).

As this study sought to examine the behavior of the highest levels of human capital, a means of identifying *star* talent had to be defined. In an effort to promote sustained publications over multi-year periods, a three-year moving average was chosen as the identifying metric. As a means of distinguishing between different levels of performance, at the STAR level, three ranks of STARS were defined. STAR1 authors were defined as those whose maximum three-year moving average was greater than or equal to five, but less than 10. STAR2 authors' maximum three-year average over the specified time period was between 10 and 15, and the most prolific authors, STAR3, had a maximum three-year moving average greater than or equal to 15. For the firms in the sample, there were at total of 977 STARS (831 STAR1s, 102 STAR2s, and 44 STAR3s. Breakdown statistics for each firm in the sample are contained in Exhibits 5-8, and presented graphically in Exhibit 9. The following section will discuss the implications of these findings.

III. STAR AUTHORS – LINK TO PRODUCTIVITY

A. STAR Authors - Introduction

In this section I explore the extent to which the scientific elite drives research productivity. At the core of this issue is the hypothesis that the high-impact research at an organization originates from those with the most talent. At many of these firms, large concentrations of revenue are derived from a small number of products. As a result, further emphasis is placed on the breakthrough research that will feed the drug development pipeline and support the firm for many years. Therefore, I seek to identify those scientists functioning at the highest levels of output, and determine whether a firm's research productivity correlates with the number of elite scientists it employs.

Zucker, Darby, and their coauthors have conducted the most extensive research concerning star scientists. Their pioneering work examined the flow of information from star bioscientists to the corporate sector that ultimately resulted in the birth of the biotechnology industry. Their work classifies star bioscientists as "those with more than 40 genetic sequence discoveries or 20 or more articles reporting genetic sequence discoveries by 1990" [1995]. One of their primary findings is that, to properly understand the way in which scientific breakthroughs and innovation shape the biomedical industry, one must focus on the activity of the elite scientist.

At first glance, both the Zucker and Darby star definition and the moving average STAR definition described above lead to similar first-order discoveries. Both analyses targeted only the elite performers. The Zucker & Darby star scientist represented the top 0.8% of biomedical scientists, while the STAR author classification herein identified the top 2.5% of publishing authors. As defined, their star's publication productivity was 22 times the average of their peers, while the STARS (STAR 1, STAR 2, and STAR3) defined by me have a productivity 11 times greater than that of their peers.

B. Star Authors -- Hypothesis

Because of the prolific nature of the star authors, and the extent to which they regularly outperform (out-publish) their peers, it was hypothesized that the number of STAR scientists at a given firm would be a relatively accurate predictor of productivity. As was found in the biotechnology industry, those scientist expanding the body of knowledge at the fringe of discovery, I hypothesize, represent the drivers of productivity for a firm. I expect to see a rather strong positive correlation between important patent output and the number of STAR scientists (after controlling for size and sales.) Also, I expect the higher-levels of STAR scientists (STAR2 and STAR3) to be stronger predictors of research productivity.

C. STAR Authors – Methods and Data

To investigate the effect of the number of STAR scientists at a given firm on the research productivity, OLS estimates were run similar to those found in Henderson and Cockburn

[1998]. For reasons of consistency with the Henderson & Cockburn sample and findings, the regressions utilized only a subset of the sample firms. Exhibit 10 identifies the firms that were included in the regression analysis. Exhibit 11 provides extensive descriptive statistics for all of the variables to be used throughout this analysis. Exhibit 12 gives summary data for these variables at five-year intervals. The number of STAR scientists at the average firm has grown from 18.0 in 1980 to 30.7 in 1994. The standard deviation in every year is greater than the mean, highlighting the widespread in the data and the skew towards zero. A recurring theme throughout this research effort, Merck represents a rather formidable outlier from the rest of the data, in that it's 175 STAR authors in 1994 is almost four standard deviations above the mean.

The dependent variable, Important_Patent_Count (as defined by Cockburn and Henderson [1998], patents granted in two of the three major intellectual property geographies (Europe, Japan or the US)) was estimated as a function of AUCOUNT (number of authors publishing at a given firm in a given year), $SALES_{t-1}$ (Pharmaceutical sales for a given firm in year t-1), STAR1, STAR2, AND STAR3. Important patent count was also estimated as a function of STAR_TOT as a means of assessing the relevance of the various levels of STAR authors. The AUCOUNT variable was included was include to control for the size of the research effort, while the $SALES_{t-1}$ variable was used to control for the overall size of the pharmaceutical firm.

As a means of smoothing the data and eliminating dominating effects brought about by outliers, estimations were conducted with both absolute and logarithmic variables. This was

especially necessary in the case of the sample data herein due to Merck's large number of STAR authors, patent counts, and pharmaceutical sales figures. Comparisons or the results of each type of estimation will suggest whether results are driven by Merck data, and whether data smoothing techniques are necessary in this analysis. The estimation regressions that were run are as follows:

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 STAR1 + \beta_4 STAR2 + \beta_5 STAR3 \quad (1a)$$

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 STAR1 + \beta_3 STAR2 + \beta_4 STAR3 \quad (2a)$$

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 STAR1 \quad (3a)$$

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 STAR2 \quad (4a)$$

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 STAR3 \quad (5a)$$

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 STAR\_Tot \quad (6a)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log STAR1 + \beta_4 \log STAR2 + \beta_5 \log STAR3 \quad (1b)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log STAR1 + \beta_3 \log STAR2 + \beta_4 \log STAR3 \quad (2b)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log STAR1 \quad (3b)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log STAR2 \quad (4b)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log STAR3 \quad (5b)$$

$$\log(Patcount) = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log STAR\_Tot \quad (6b)$$

Patcount – The annual number of *important patents* received by a firm

AUCOUNT – number of authors publishing from a given firm in a given year

$SALES_{t-1}$ – the total pharmaceutical sales in the previous year ($US-1994)

STAR1 – Authors w/ maximum 3-year moving average paper count between 5 and 9.9 papers per year.

STAR2 – Authors w/ maximum 3-year moving average paper count between 10 and 14.5 papers per year.

STAR3 – Authors w/ maximum 3-year moving average paper count of 15 or greater.

STAR_Tot – The Sum of Star1, Star2, and Star3.

D. STAR Authors – Results & Discussion

Exhibit 13 contains the results of the level-variable estimations while Exhibit 14 contains the results from the log models.

The estimations run with absolute variables show a positive correlation between research productivity and STAR authors. It should be noted that the four STAR scientist variables (STAR1, STAR2, STAR3, and Tot_ STARS) have very high correlations for independent variables, and further analysis on this topic will follow. However, taken literally, the data show that each additional STAR1 scientist added about one *important patent* per year. STAR2 scientists added, on average, and additional 7 important patents per year, while STAR3 scientists added approximately 10 excess patents per year. This is extremely supportive of the hypothesis that the STAR variable would be an excellent predictor of research productivity at the firm. The t-statistics for the three models that contained only one STAR variable, Equations 3a, 4a, and 5a are 4.7, 6.1, and 4.5 respectively. Coupled with the coefficient estimates, this is somewhat supportive of the secondary hypothesis, that the higher levels of STAR authors are additional drivers of the productivity of a research program. The large coefficient estimated for the STAR2 variable, 7.37, with a t-statistic of 6.1 exhibits strong correlation with research productivity. These estimates would seem to suggest that STAR2 authors are extremely predictive of high levels of research performance. As a future area of study, closer examination into the cause of this strong dependence would be extremely valuable and informative. Perhaps there exists an optimal level of publication, somewhere near that of the STAR2 author cohort, which promotes the

highest levels of research productivity. Any increases above that level, it could be hypothesized, reduces the marginal benefit of publication, weakening the productive capacity of the research. Additional investigation as to strong dependence of productivity upon STAR2 scientists would be a fascinating avenue to pursue in the future.

One factor of particular significance for each of the above estimates is that patent output is negatively correlated with the AUCOUNT variable. One interpretation would suggest that the quality of the research is much more important than is the quantity, and that diminishing returns-to-scale exist in pharmaceutical research.

The $Sales_{t-1}$ variable, which was included as a control for the size of the R&D effort at a given firm, shows positive correlation for each of the logarithmic model estimates. Where statistically significant, for the absolute models, the correlation was also positive. The underlying meaning of a positive correlation with a size-control variable is that a positive returns-to-scale economy is present. As a side-note, this lends credibility to the large push for consolidation that existed in the industry for the years following 1994, as well as for the half-dozen sample firms that were involved in mergers and acquisitions over the period 1980-1994. (Exhibit 1 contains information regarding mergers among the sample firms.)

To clarify, however, the AUCOUNT and $SALES_{t-1}$ variables are both, in some way, controls for size. The same econometric phenomenon that exists in the highly-correlated STAR variables could be influencing the two size-control variables as well. The correlation between AUCOUNT and $SALES_{t-1}$ is 0.84, very close to the conventional distinction

between endogenous and exogenous variables. However, results of individually estimated regressions, where only one size-control variable was included, suggested positive correlation with $SALES_{t-1}$, yet negative correlation with AUCOUNT.

The initial model, which included all 3 STAR variables (Equation 1b,) showed a positive correlation with Log_Sales and Log_STAR2, and negative correlation with Log_aucount and L_STAR1. The results are problematic due to the high correlation between the STAR variables. However, in the case of the logarithmic models, the individual regression estimates, which contained only one STAR variable (2b-4b,) failed to show statistical significant correlations between individual STAR variables and research productivity. The fact that the results of estimating the logarithmic model do not show statistically significant correlations for STAR1, STAR2, STAR3, or Tot_STAR as individual variables suggests that the variable smoothing resulting from the log-estimation softens the effect of Merck's high productivity. This highlights an interesting point. For a number of these models, the Merck data seem to drive much of the regression analysis. The dependence of an econometric model on the data of one outlier is not usually the sign of a good model. However, in the case of Merck and the pharmaceutical industry, because Merck is such a powerful presence in the pharmaceutical research field, there is a tendency to allow such an outlier to heavily influence the models.

In their analysis, Cockburn and Henderson found no statistically significant correlation of research productivity with a "'star' system". As defined in their analysis, the *star system* variable is the percentage of publication output attributable to the top one-tenth of all

publishing authors at a given firm. The authors maintain that the statistical insignificance "may simply reflect that this variable, or any similar measure of the presence of 'stars', is necessarily very noisy, and data problems leave [them] unconvinced that [they] are measuring it properly" [1998]. I feel that the methodology and results presented here eliminate many of the data problems that the authors were referring to, and that STAR authors are very predictive of research productivity.

As the results show a positive link between STAR scientists and research productivity, an examination of individual firms helps identify those firms who tend to promote the creation of STAR authors and those that seem to retard their development.

Normalizing these STAR scientist data by the number of authors publishing at a given firm (Exhibit 15) gives a measure of the extraordinary ability of a firm to generate STAR scientists – STAR Intensity. The firms with high STAR Intensity values are consistent with those firms identified in the literature and popular press as being pro-publication. Merck, Abbott Laboratories, and Upjohn are typically associated with high-levels of basic research. One factor to note is the jump in STAR scientists that developed out of the merger of Bristol-Myers and Squibb. The weighted-average of the STAR intensities for the pre-merged firms is 4.0. By 1994, the merged firm, B-M-S, would have had a resulting STAR intensity of only about 5 or 6 had it followed industry growth patterns, and grown about 8% per year. In actuality, the STAR intensity for the merged firm in 1994 was 17. It is hypothesized that the jump was caused by a shift in publication focus that accompanied the merger. This is a question that will be pursued with members of these firms in the

qualitative interview section of this research, and would be an interesting topic to pursue in further work.

For each firm, the scatter-plot in Exhibit 16 shows the number of STAR authors per 1000 authors versus the total number of authors publishing. Firms above the trendline demonstrate an ability to *create* STAR authors (as a percentage of their entire author population) more effectively than those firms found below the trendline. The results are consistent with previous findings and conventional wisdom throughout the industry. Firms typically know as high-science (those that vigorously pursue research in the areas of basic science), such as Merck, B-W, Upjohn, and Abbott are found far above the trendline. Their ability to promote STAR creation would be an interesting subject to pursue at a later date. The firms that are not typically know for a dedication to basic science research, Hoechst, Hoffman, Bristol-Myers, and Squibb are indeed found below the trendline, highlighting their STAR -impeding nature.

Normalizing the STAR data by a control variable for the overall size of the firm, $SALES_{t-1}$ gives a one measure of productivity, though with a considerable time lag. Exhibit 17 contains firm-level statistics for STAR scientists per $1B ($U.S., 1994). The same groupings of firms exist in these data as well; however, Merck drops to fifth. Of considerable significance is the overall spread in the data, with some firms possessing more than 15 STAR authors for every $1B in pharmaceutical sales, yet nine other firms have less than five STAR scientists per $1B in revenues.

Another interesting way to view this phenomenon is through the scatterplot in Exhibit 18. The ordinate axis contains the total STARS for a given firm divided by total pharmaceutical sales in 1994. One interoperation is that there exists an optimal level of research dedication. The shaded area in Exhibit 18 was drawn somewhat arbitrarily, yet based on a general sense of corporate performance over the past two decades. Those firms that are located near or inside the shaded area (Merck, Pfizer, Glaxo, etc.) have demonstrated the ability to develop profitable drugs and generate value for their shareholders. One interpretation is that the firms above the shaded region (B-W, Upjohn, Abbott, etc.) are too dedicated to the pursuit of basic research. This may not suggest that the aggregate level of research is too high, but that the ability of those ventures to generating profitable products is less efficient. Finally, those firms in the lower right quadrant of the scatterplot seem to be less likely to create STAR scientist per dollar of sales, and can be thought to have too low of a dedication to basic science research.

V. STAR Authors - Conclusion

As a predictor of research productivity, human capital quality as measured by publication frequency has been shown to be fairly effective. The fact that the scientific elite is strongly linked to productivity sheds light on some very important human resource management practices. While recent management paradigms in organizational effectiveness have de-emphasized the ability and aptitude of the individual in favor of positive group dynamics and structure, the results of this study call some of these practices into question.

These findings have far-reaching effects into hiring and employee retention issues inside of the research organization, as well. If an excessive share of the research productivity of an organization falls on the shoulders of a few key scientists, perhaps the recruitment of the elite scientists from other firms would be a value-creating endeavor. On the other hand, perhaps a pro-publication culture within a firm would re-focus the research efforts on the exploration of basic science as opposed to strict concentration on the development of previously identified drug candidates. Scientists have communicated with me that some firms have an internal aversion to publication by their scientists. Managers at some of the sample firms have told STAR scientists that authoring of journal articles should be conducted on "free-time, " or when development work was slow. With STAR authors having been shown highly correlated with patent output, I would tend to question the reasoning behind these corporate practices.

However, one aspect not captured by this analysis is the amount of support given to highly prolific scientists from employees and resources inside the firm. An examination of the productivity per factor input (labor and capital), that controlled for the number of employees staffing the research labs or the amount of capital resources dedicated to a STAR scientist, would be valuable and revealing.

IV. HUMAN CAPITAL – LINK TO PRODUCTIVITY

A. Human Capital – Introduction

This section pertains to the same basic question as the previous: How important is the quality of human capital in predicting the research productivity of a pharmaceutical firm? However, here human capital is measured differently than above. In this chapter I examine the innate quality of human capital, quantified in a manner independent of a scientist's performance in the industry. The STAR variables, above, identified those scientists who performed at a high level after entering the industry. On the other hand, a quantification of human capital, which identifies the aggregate intelligence level of the scientists at a firm, has entirely separate implications for the firm. The results of this section provide insight to the tradeoff between experience and innate ability made by managers and recruiters.

Also, I sought to examine whether the use of publication data in fact merely mimicked productivity data or if it actually served as a suitable predictor variable. The ideal measure of human capital would capture the innate intellectual ability of the scientists, as well as firm-specific knowledge. As described below, I utilize a database of PhD dissertations and abstracts as a means of constructing a human capital variable with lower correlation to the TOTAL_STAR variable. Though the method contained herein does not measure firm-specific knowledge, it represents a common means of evaluating innate intellectual ability, and because of its lower correlation with the TOT_STAR variable, reduces the likelihood of an endogenous model.

B. Human Capital – Hypothesis

It was hypothesized that the aggregate quality of human capital would also be a predictor of R&D productivity, as measured by important patent output. However, because it was also hypothesized that the STAR variable picked-up an element of endogeneity, it was hypothesized that the HUM_CAP variable would be have a weaker correlation, and be less predictive of research productivity than are the STAR variables.

C. Human Capital – Methods & Data

Initially, a patent query was run in order to determine each of the author's first name. A combinational query, containing the author's last name, initials, and firm-name was submitted to the United States Patent and Trademark Office website (http://www.uspto.gov/). In roughly one-third of the cases, the first name of the author was able to be determined from the queried patents. Knowledge of the author's first name aided greatly in clarifying multiple listings in the dissertation abstract database, and served to clarify many ambiguities that arose during the subsequent steps.

UMI Dissertation Database – For each author, the UMI Dissertation Abstract database was used to identify the college or university that granted the scientist's Ph.D., the year of graduation, and the area or subcategory of the research. In the case of multiple listings for a given author name/initial, the research area was used to identify the proper candidate. In

cases where ambiguities arose due to multiple listings in the areas of chemistry, biology, or other natural sciences, the author's graduate education information was omitted.

Once all available knowledge had been gathered for each of the STAR authors, a means of ranking the quality of human capital needed to be determined. A pioneering study performed by Berelson [1960] ranked the graduate institutions in the United States into four broad classes (Top Ten, Next 12, Body of Universities, Remaining Schools). These graduate school rankings have been used to measure aggregate human capital by multiple studies over the past 40 years, but most have pertained to human capital quality among corporate managers or humanities/social science academics. It was believed that Berelson's rankings were aptly suited to categorical ranking in liberal arts and the social sciences, yet researchers were tentative to use these rankings in the context of technical or scientific professions. Also, researchers had begun to question whether Berelson's rankings were current, and whether they applied to particular disciplines or professions. In response to this lack of current data, the National Research Council undertook the huge project of ranking individual department and schools for the vast majority of graduate institutions in the United States (Jones, et al, [1982]).

One aspect of the graduate school study conducted by the NRC was a reputational survey of 1848 faculty members in the area of "biochemistry, botany, cellular/molecular biology, microbiology, physiology, and zoology" (Jones, [1982a], [1982b], and [1982c].) The survey results were analyzed and sorted by the NRC to produce various ranking metrics.

The ranking that I used to quantify the quality of human capital at the sample firms was the "*Mean rating of the effectiveness of the program in educating research scholars/scientists.*"

The Jones study has gained wide acclaim for thoroughness and accuracy, and has been cited by numerous studies across numerous disciplines. Addenda and slight technical criticisms notwithstanding, academics attested to the study's robustness and accuracy.

Every STAR author included in the UMI Dissertation Database was given a human capital quality score according to the university or college granting his/her Ph.D., on the basis of the *mean rating of the effectiveness of the program in educating research scholars/scientists* for that college or university. The mean score for the STAR scientists in the sample was 2.1 ($\sigma = 0.49$), compared with a population mean of 1.7 ($\sigma = 0.50$). Summary data are included in Exhibit 12 and a histogram of human capital quality is shown in Exhibit 19.

Resulting from the global geographic dispersion of the sample firms, the human capital data for some firms was relatively sparse. Firms located outside of the United States had relatively few STAR authors whose graduate education data could be found in the UMI Dissertation Database. For the firms that had less than 10 human capital data points, authors slightly below STAR status where examined in an attempt to expand the set of authors and increase the precision of the human capital measurements. With the exception of Japan's Fujisawa, a minimum of 10 data points was obtained for each firm in the sample. Utilizing data derived from authors whose publication level was less than that of the STAR authors would seem to downward bias the human capital scores. However, it was felt that the hiring

practices and Ph.D. demographics inside of a given research lab would be rather consistent. Additionally, the scientist used to augment the data had a mean *Maximum 3-Year moving averages* (the metric used to identify STAR authors) of 3.8, just slightly below the level to be considered as a STAR author. In short, it was believed that the additional scientists were of similar background and publication performance as the STARS, and that the inclusion of their human capital scores was accurate and justifiable. Exhibit 19 includes the augmented data, and highlights the change in measured human capital levels due to the expanded data set.

Human capital rankings were averaged across every author associated with a given firm, and for every year 1980-1994. A particular author's human capital score was only included in the average if he/she had published at least one paper for that year. The breakdown of human capital ranking by firm by year from Exhibit 19 is depicted graphically in Exhibit 20. As this exercise was conducted in order to reduce the somewhat endogenous nature of the TOT_STAR variable, it is interesting to note that the correlation between the two variables is 0.46. I think that this represents an acceptable level of correlation. As both are "positive" variables that were not expected to be totally uncorrelated, a positive yet moderate level of correlation is what was expected and will serve as an excellent variable to use for the productivity estimation.

Comparing the firm-level STAR statistics (Exhibit 9) with the firm-level Human Capital statistics (Exhibit 21), one will notice that the ranking of the firms is only moderately

comparable, another indication that the human capital variable captures information not found in the STAR author data.

One particular point of interest is that fact that human capital quality (Hum_Cap_Adj) was greater than the mean for only four firms (Abbott, Upjohn, Merck and Beecham.). These firms are known for a high level of dedication to science and basic research, both in the literature (Cockburn and Henderson [1998]) and among market analysts.

Finally, Important_Patent_Count was estimated as a function of the variables: AUCOUNT (the number of distinct authors for a firm in a given year), Sales(-1) (the total revenue generated from pharmaceutical sales in the previous year), and Hum_Cap_Adj (the adjusted measure of human capital per firm per year with the augmented data source for firms with less than 10 STAR scientists with known human capital rankings). Again, both level and logarithm models were estimated.

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 HUM\_CAP\_ADJ \quad (7a)$$

$$\log Patcount = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log HUM\_CAP\_ADJ \quad (7b)$$

Patcount – The annual number of *important patents* received by a firm

AUCOUNT – number of authors publishing from a given firm in a given year

$SALES_{t-1}$ – the total pharmaceutical sales in the previous year ($US-1994)

HUM_CAP_ADJ – average human capital quality score for a firm in a given year (includes adjusted data)

D. Human Capital – Results & Discussion

The results of estimating equations (7a and 7b) are included in Exhibits 22 and 23. As hypothesized, both models suggest a positive correlation between research productivity and the quantified measure of human capital at a given firm. The nearly identical t-statistics (2.27 and 2.33, respectively) are somewhat reassuring in that the data omitted for the log-model did not affect the fit of the data to a large extent. Also, as expected, the R-Squared value for each of the estimations was less than that for the STAR variable estimations. For the absolute model, each additional 0.1 increase in the Adjusted_Human_Capital variable results in and additional 5 important patents.

As with the STAR variables, it is suspected that the data for Merck are powerful driving factors in the estimation models. The R-Square value for the logarithmic model is half that found when estimating with absolute variables, suggesting that the data smoothing reduced the result-driven dependence on the data outliers.

Though it was hypothesized that human capital level would be an adequate predictor of research productivity, I was concerned with the extremely high human capital quality of the pharmaceutical scientists as a group. Going back to Exhibit 19, the median scientist in the sample had a human capital score that ranked at the 86 percentile of the population as a whole. With such a skewed sample set, I wondered if the human capital variable constructed from the NRC study had enough precision at the high end of the scale. As the results show, the NRC study afforded enough precision to highlight statistically significant

human capital scores as indicators of research productivity. An area of future study that would be very elucidating would be an attempt to quantify the firm-specific knowledge dimension of human capital. As mentioned, a perfect metric of human capital quality would include both innate intellectual ability (as measured here) and firm-specific knowledge. Qualitative interviews would provide an excellent means of quantifying the firm-specific knowledge that a research lab cultivates and utilizes to promote productivity.

V. Human Capital – Conclusion

The results presented in this section, that research productivity is positively correlated with human capital, have far-reaching implications. As it pertains to corporate policy, these findings are even more significant than those presented in Chapter IV. Previously, I maintained that although it is trendy to focus on organizational drivers of productivity, the fact that the quantity of elite scientists has been linked to productivity suggests that human capital quality may be a better indicator. In this section, I maintain that high levels of natural or innate human capital are also predictive of higher productivity. Such findings support the recruitment of researchers from the universities with strong academic reputation. Although the use of regression statistics in this manner is tenuous, it could be interpreted that hiring scientist only from tier-one universities rather than the median program would increase productivity by 24 important patents per year, a quite large increase in productivity, to say the least. With human capital playing such a deterministic role, the findings above would seem extremely useful to managers in the pharmaceutical industry.

V. HUMAN CAPITAL MOVEMENT – The Pharmaceutical Industry Perspective

A. Introduction

As shown, human capital can have a tremendous effect on research productivity. That being the case, the following two chapters investigate the movement of this precious resource. This section quantifies the overall level of human capital movement between firms in the industry, and describes the labor market that dictates this level. Understanding the forces that govern the labor market enables a firm to position itself so that it can best fulfill its needs for labor. A discussion will follow that examines some of the structural and personal obstacles that impede the movement of STAR scientists. Once the industry-wide barriers have been identified, firms can adjust the personal and structural aspects of working for their firm so that they maintain a labor demographic deemed optimal. For instance, a firm wishing to increase the level of human capital movement in and out of its research laboratories can attempt to decrease the average project duration, thereby decreasing the amount of firm-specific knowledge possessed by an employee. On the other hand, a firm wishing to keep tight control of it pool of scientific labor could seek to increase the portion of personal capital an employee has vested in the firm, either via stock-options programs or by giving employees 'implicit ownership' of a particular stream of work. The next chapter will discuss the ways in which these levels of human capital movement affect productivity.

At the fundamental economics level, a vast literature exists on human capital as an economic input, and its ability to move about freely in an economy. Also, considerable work

has been done examining the boundaries that serve as market imperfections inhibiting the free flow of human capital as factors of production. With such a large body of literature on both subjects, it seems striking that few have attempted to quantify levels of human capital movement and turnover for various industries.

Arthur and DeFillippi [1995] describe an evolving model of the labor market in high-tech, information intensive industries. Drawing upon the work of numerous others, they describe the development of a nearly efficient labor market that has been (or, in some cases, is being) created for high-tech industries such as pharmaceuticals. The *Boundaryless Culture*, as they have called it, is marked by high-levels of human capital movement caused by structural shifts and employee psychological changes. I examine whether the levels of human capital movement predicted by Arthur, et al are consistent with those I find for elite pharmaceutical scientists.

Because the biotechnology and pharmaceutical industries have such a large number of similarities with the microelectronic/computer industry, Gunz's [1999] study of the movement of managerial human capital in the Canadian Biotechnology Industry (CBI) provides an excellent benchmark case for comparison. Although this study focused on the top five managerial positions at the firm, and not the research scientist positions, the organizational boundaries that existed (or failed to exist) may pertain to the STAR authors as well, and are worth noting. Additionally, one of the five managerial roles included in Gunz' study was the *Head of Research and Development*, a position that *could* be interpreted as somewhat analogous to the *star* scientists examined by this study.

Gunz [1999] found that "surprisingly little movement seems to be taking place." Gunz found as few as 14 out of a total of 2256 (0.6%) of the managers had switched to another biotechnology firm in the sample over the time period 1991-1997. Gunz's identification of the Canadian Biotech Industry as one of the industries with high impedance to human capital movement establishes a baseline to which I will compare the movement of human capital in the pharmaceutical industry.

At the other end of the spectrum, the Silicon Valley region in California represents the paradigmatic case for those describing a boundaryless labor market. As the region developed as the hotbed of activity for the microelectronic industries in the United States, researchers interested in the flow of human capital immediately grasped the importance of the development in that labor market. For numerous reasons, the boundaries impeding the flow of human capital deteriorated. It can even be argued that structural and personal forces exist in the Silicon Valley labor market that promote the flow of human capital above and beyond levels justified by factor-input economics.

In as study of the labor market mobility of engineers of the U.S. semi-conductor industry, Angel [1989] examined the ease and frequency of human capital movement. From a survey sent to 800 semi-conductor engineers at 67 firms scattered throughout the U.S., Angel constructed turnover and inter-firm mobility measurements similar to Gunz' study of mangers in the CBI. Angel found that the 275 engineers accounted for 209 inter-firm movements over a period of seven years (1980-1986). While the semiconductor firms in

this analysis are found across the U.S., over half of the inter-firm movements of human capital were between two Silicon Valley semiconductor firms. However, a considerable number (71 (34%)) of these employment changes involved moving across state boundaries. (Angel [1989]).

With the above cited examples as points of reference, the study herein provides much needed data in the area of employee turnover and human capital movement and serves as a springboard to a discussion of the personal and structural nature of the market for labor among elite pharmaceutical scientists.

B. Hypothesis

It was hypothesized that the movement rates would be extremely low, dwarfed by the movement rates of Silicon Valley firms, and the same order of magnitude, but slightly higher than the managers of Canadian Biotechnology Industry. I believe that the firm-specific knowledge component of the scientist's human capital, coupled with the length of time dedicated to a pharmaceutical project, imposed too many restrictions to employee movement to see levels as high as Silicon Valley. On the other hand, while CBI managers exhausted tremendous energy in building intra-firm relationships (as shown by their ascension to high positions inside of the firm), the STAR pharmaceutical scientists are more concerned with the advancement of knowledge and publication in their field. This distinction leads me to hypothesize slightly higher turnover rates for the pharmaceutical scientists than for managers in the CBI.

C. Methods & Data

For each STAR scientist, an "*elapsed-time* in the data set" was calculated by subtracting the year of that scientist's first publication from the year of his/her last. Scientists were categorized according to their elapsed time in the data set for reasons of comparison. This was because the inherent probability that a STAR scientist would move to another firm varies with the total time spent in the industry. Of the 976 STAR authors, 197 (20%) were present in the database for the entire 14 years, and almost half (457 authors (47%)) existed in the data for 10 years or more. Each scientist was examined for the number of cross-firm movements he/she made over the sample time period.

D. Results & Discussion

Exhibit 24 contains the results of that study, and summarized findings from the Gunz Canadian Biotechnology Industry study and Angel's study of semiconductor engineers. The level of inter-firm movement for pharmaceutical researchers was somewhat surprising. A total of 55 authors made one move, while 12 authors moved twice, and 3 authors crossed firm boundaries 3 times. These results indicate that 9% of all STAR scientists switched between firms in the sample over the time-period 1980-1994.

Discussion will follow that will attempt to give some perspective as to the scale of a 9% movement rate, but at present, it should be mentioned that a rate 15-times that found in the

Canadian Biotechnology industry was not expected. Also, closer examination of those STAR scientists that existed in the data for 10 years or more reveals that the inter-firm movement rate for this cohort as high as 13%, with 60 movements out of 457 total authors.

On the other hand, however, the movement statistics for the pharmaceutical industry can not compare to the 76%-level Angel found among semiconductor engineers. The geographical nature of the pharmaceutical industry alone, with the 20 sample firms dispersed around the world, is enough to render a movement rate of 76% nearly impossible.

Structural and Personal Factors Affecting Inter-firm Movement Rate

In achieving one of the five most prominent positions at a Canadian Biotechnology firm, an employee must build considerable firm-oriented human capital. This would seem to indicate, although the industry is still in its early stages, that a large portion of the manager's effort would be aimed at constructing positive political relationships inside of the firm. On the other hand, a pharmaceutical scientist's incentives and objectives are not dedicated to the firm alone. As will be covered in the interview section to follow, often the pursuit of a prolific publication schedule must be conducted on a researcher's free time. Only after intellectual property protection has been firmly secured can an author publish findings, and often much of the work in authoring these papers must be conducted on top of the researcher's clinical schedule.

Becker, Oi, Parsons show that the acquisition of skills that are firm specific lead to low turnover rates. Because much of the pharmaceutical industry is segregated into drug or

therapeutic classes, these STAR scientists tend to acquire much more firm specific knowledge than would an engineer in the semiconductor industry working on a short-term project. Scott [1987] and Storper & Christopherson [1987] describe how the acquisition of job skills that are industry specific, as is the case for the engineers, leads to a "pattern of frequent job changing ... in which highly skilled professional workers move between firms in a series of short-term employment contracts.

Also, a STAR scientist at one of the sample pharmaceutical firms, by definition, has dedicated a tremendous amount of effort to advancing himself/herself in the broader community, through publications. This would be a large contributor to the higher movement rate among research scientists, as they are clearly less firm-centric than would be a manager in the CBI.

V. Conclusion - Human Capital Movement

The above discussion was intended to provide a background of the literature on the subject of aggregate human capital movement rates for various industries. It was not meant to establish any conclusions with respect to the pharmaceutical industry labor market for elite scientists, but only to touch upon the ideas present in the literature. However, the issue of employee retention is important to every organization. More often than not, an organization that relies heavily on highly skilled employees faces the challenge of retaining its best workers. An understanding of the inhibitors of perfect employee mobility in a market for labor enables the firm to address the issues that most affect that organization. Here, the

pharmaceutical industry exhibits relatively low impedance to human capital movements, and the retention of these skilled scientists is the paramount issue affecting most of these firms in the 1990's. In a contradictory fashion, keeping the elite scientists employed by a company has become one of its primary objectives, yet the information flow that comes with high employee turnover is hypothesized to enhance productivity.

V. HUMAN CAPITAL MOVEMENT – A Pharmaceutical Firm's Perspective

A. Introduction

Most managers, whether it is conscious or not, take a resource-based view of the firm. As described, a firm represents the aggregation of many kinds of resources, be they labor, capital, knowledge, or technology. In the resource-based model, the process of building innovative capability involves pooling together assets in the most effective manner possible. From the manager's perspective, acquiring talent from within the industry is one way in which he/she meets the resource needs of the firm.

For each of the sample firms, I examine its contribution to the overall level of human capital movement. Some firms are highly central to this flow, with a large percentage of the total movements either originating or ending there. On one level, these movements affect productivity in the manner described above, by adding resource talent to the research labs of a given firm. On a higher level, these movements represent a tremendous flow of information from one firm to another. The knowledge base of firm that a scientist joins is greatly expanded, and I examine whether both of these phenomena have a positive impact on productivity.

Angel [1989] suggests that the very high level of human capital movement among semiconductor engineers serves as an excellent conduit for the flow of industry-wide and

firm-specific information. As spillovers derived from the flow of information via organizational networks or collaborative efforts have been shown to be significant drivers of research productivity in the pharmaceutical industry, (Henderson and Cockburn [1993], Acs and Audretsch [1988, 1993], Jaffe [1989], Jaffe, Trajtenberg, and Henderson [1993], Acs, Audretsch and Feldman [1994], Griliches [1992]), I aim to show that human capital movement can have the same effect. Through this study I hope to identify inter-firm personnel movements as an additional vehicle for productivity enhancement, brought about by increased information flow.

As mentioned, Zucker and Darby contend that a considerable amount of the value that comes with each scientific discovery is embodied by the tacit knowledge gained through participating in the discovery. As the pharmaceutical industry pushes towards the biotechnology arena and away from its historic small-molecule roles, this tacit knowledge becomes increasingly important. Further, it begs the question as to the efficiency and effectiveness of publications as the medium of information flow. This phenomenon is magnified "when the discovery – especially an 'invention of a method of discovery' – is sufficiently costly to communicate due to its complexity or tacitness. This results in a situation where the information can only be effectively used by employing those scientists in whom it is embodied" (Zucker and Darby [1995]). STAR scientists are inherently at the apex of pharmaceutical innovation, as they sit at the very forefront of scientific advancement. The amount of *traditional* and *tacit* knowledge that they acquire is tremendous. The act of communicating this information to collaborators or assistants is difficult, thus there are tremendous gains to be made from the acquisition of a STAR

scientist. I seek to determine if the addition of this firm-specific and tacit knowledge to the existing knowledge base inside the recipient firm results in increased research productivity, as predicted by Zucker and Darby [1996a].

As tacit knowledge is accumulated in the research laboratories of pharmaceutical firms, it becomes interesting to investigate the range of media via which it can be transferred to other institutions (be they universities, hospitals, or other firms in the industry). Outside of explicit research collaborations among scientists from different institutions, it would seem that the only other way to transfer the truly tacit knowledge would be through movements in human capital, for, as described above, publications are unable to capture the tacitness and complexity that accompany innovation in this industry. Further, it is hypothesized that a firm's position in the network of human capital movements also provides a positive boost to research productivity.

Considerable research has been conducted regarding organizational networks as drivers of productivity in numerous industries. Conclusions of such research state that in highly technical and scientific industries, the locus of expertise and skilled research are spread among firms in that industry, and that a network between these areas of expertise, capable of harnessing and managing it effectively, greatly aids innovation. It is interesting to note that many of the hypothesized causes of the enhanced ability to innovate can be applied to the area of human capital transfer:

Learning: The movement of human capital represents the extreme case in access to information. Compared with the flow of information from a research laboratory via journal articles and partnership arrangements, the movement of a STAR scientist from a position at one firm to another represents information flow a level of magnitude greater. The acquisition of a STAR scientist privileges an organization to not only the vast amount of scientific knowledge possessed by that scientist, but also the tacit knowledge built over numerous years of extremely high levels of scientific attainment. Stinchcombe [1990] and Nelson [1990b] separately state that the organizational arrangements that are the most beneficial to its participants provide excess access to timely information. Angel suggested that the high level of mobility of semiconductor engineers served as a "conduit for the rapid dispersal of knowledge and manufacturing skills among Silicon Valley firms" [1989]. The access to such information is one of the fundamental drivers of competitive advantage in dynamic industries [Nelson 1990a]. The accelerated flow of information "contributes to the innovative capability and technological dynamism of production complexes" (Aydalot and Keeble [1988] and Stohr [1986]).

Practicing: To capitalize on the available knowledge (whether acquired via a collaborative network or through the addition of a STAR scientist) a firm must possess the skills to exploit that knowledge. Scientists with practical knowledge that differs from the institutional base at a given firm increase the probability that available knowledge can be applied in productive ways. Brown and Duguid [1991] summarize by saying that enhancements in productivity and innovation are result from "becoming a practitioner, not learning about practice." In this way, the addition of a STAR scientist, with the tacit

knowledge of "doing" in a manner differently than that normally found at that firm, enables the firm to better implement knowledge and ideas through alternate channels. I believe that this phenomenon also serves to enhance research productivity.

B. Hypothesis

As was described previously, human capital is of immense value to the research arms of pharmaceutical firms. As a stock variable, the aggregate level of human capital at a firm is a considerable asset. Additionally, as described above, the flow of human capital into a firm can have a compounding effect, as tacit knowledge added in the area of a new technique or new method of discovery can have a multiplicative effect on the overall level of human capital within a firm.

Companies that acquire STAR scientists from outside the firm boundary greatly augment the tacit knowledge and learning capability of that research institution. The arrival of a STAR scientist results in a spillover of the knowledge, techniques, and procedures that increases the capacity of that organization to conduct basic research. This knowledge is utilized by the firm over a period of time, and is absorbed into the research capability of that institution. It is hypothesized that research productivity is a positive function of the number of STAR scientists joining a firm from outside of its boundaries.

Also, the research productivity of firms that are centrally located in the network of human capital movements is higher than disjointed firms due to the positive effects felt by the

augmentation of the tacit knowledge base. While the first hypothesis addresses first-order movements of human capital, the second, network centrality, includes higher order human capital transfer effects. Fundamentally, a STAR scientist from a firm central to the human capital network would possess a broader, higher-level of knowledge than a STAR scientist from a firm unconnected to the human capital flow network. The benefits from increasing information flow and the transfer of tacit knowledge result in an increase in the research productivity of a given firm. Therefore, it is hypothesized that productivity is a positive function "measures of centrality in the human capital flow network."

C. Methods and Data

Two measures of firm-level human capital movement variables were constructed from this database.

(i) firm specific STAR -scientist additions by year

$$Movement\_A_{i,t} = M_{i,t}$$

(ii) as hypothesized, the tacit knowledge brought by a STAR scientist could possibly enhance research productivity for a number of years following the move. For this study, I constructed and tested a variable that accounted for the possibility that the benefits felt from the addition of a STAR scientist last for three years following the move. Therefore, the Movement_B variable represented the sum of movements into a firm over the past three years. Understandibly, variables for 1980-1981 contain additions to the firm for which data is available.

$$Movement\_B_{i,t} = \sum_{t-2}^{t} M_i$$

Exhibit 25 gives summarized movement data for the sample firms, while Exhibit 26 contains a graphical depiction of the additions of STAR scientists from other firms in the sample. Noticeably, over half of all of the movements to the 20 sample firms in the sample go to one of four firms

Secondly, a network-style database was constructed from the human capital movement statistics. The database differed from those constructed in social network analyses in that flows were modeled as unidirectional, as opposed to the typical bi-directional network. In a conventional social network, each node benefits to some extent through its connection to other nodes. For this case, the modeling of human capital movement as the transfer of tacit and other specialized knowledge, the *receiving* node had the potential to benefit from the movement, while the *giving* node does not. For the time-period 1980-1994, each firm was scored according to the number of STAR scientists who joined the firm (+1 for each STAR scientist additions in that year). It should be noted that the year used to identify the movement of a scientist was the first year in which that scientist published with the new firm. This date was chosen due to the fact that a scientist tended to be found on the author list of works long after his/her move to another firm. The often-times lengthy article review process, coupled with the tradition of citing numerous authors with varying degree of contribution to a given article, results the possibility that an author could show publications at a given firm 2 to 3 years after his/her departure.

Central connectivity in the human capital movement network – central connectivity statistics were calculated for each of the 15 years. Central connectivity is a measure of the extent to which a given node in a network is connected, either directly or through other nodes, to the other nodes in the network. The UCINET network software package was used to calculate the central connectivity ($CENTRAL_t$) figures for each firm in the sample (Borgatti, Everett, and Freeman [1992]). The centrality measures were then normalized to the interval [0,1]. Descriptive statistics of the central connectedness variable CENTRAL are contained in Exhibit 12. A firm-level graphical depiction of these data is included in Exhibit 27.

I conducted OLS estimates of the effect of central connectedness on research productivity in much the same manner as done above for human capital quality. Important_Patent_Count was estimated as a function of the two movement variables and the firm's central connectivity score at a given year. Corrections were made for the total number of authors (AUCOUNT) and $sales_{t-1}$ (SALES(-1)). The following models were estimated:

$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 MOVEMENT\_A \quad (8A)$$
$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 MOVEMENT\_B \quad (9A)$$
$$Patcount = \alpha + \beta_1 AUCOUNT + \beta_2 SALES_{t-1} + \beta_3 CENTRAL \quad (10A)$$

$$\log Patcount = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log MOVEMENT\_A \quad (8b)$$
$$\log Patcount = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log MOVEMENT\_B \quad (9b)$$
$$\log Patcount = \alpha + \beta_1 \log AUCOUNT + \beta_2 \log SALES_{t-1} + \beta_3 \log CENRAL \quad (10b)$$

Patcount – The annual number of *important patents* received by a firm

AUCOUNT – number of authors publishing from a given firm in a given year

$SALES_{t-1}$ – the total pharmaceutical sales in the previous year ($US-1994)

Movement_A – the number of star scientist additions in a given year

Movement_B – the number of star scientist additions over the previous 3 years for given firm

CENTRAL – the central connectedness of a firm in the human capital movement network

While conducting this analysis, I have collected data detailing the place of employment for the STAR scientist prior to joining the sample firms, and after departing these firms. I think an excellent area of study would be to examine research productivity effects as a function of central connectedness variables for other networks, similar to that done by Zucker and Darby for the biotechnology industry. I have grouped the data into eight broad categories: top-tercile universities, mid-tercile universities, bottom-tercile universities, hospitals, public (according to the Cockburn and Henderson [1998] definition), the NIH, industry (outside of the 20 sample firms) and other. I include these data in appendix B as a means of providing access to these human capital movement statistics should they be needed in the future.

Exhibit B1 – Industry-wide pre- and post-employment statistics

Exhibit B2 – Employment statistics prior to joining the pharmaceutical industry

Exhibit B3 – Employment statistics after departing from the pharmaceutical industry

Exhibit B4 – Graphical firm-level data – Place of employment prior to entering the pharmaceutical industry.

D. Results & Discussion

Results of the OLS regressions are contained in Exhibits 28 and 29. The estimation results do not show statistically significant correlation between research productivity and either of the two direct movement variables (Movement_A: EQ9a & EQ9b; Movement_B EQ10 & EQ10b). Additionally, no statistically significant correlation was found for the centrality variable in the logarithmic model. However, positive correlation was found to persist between the research productivity of a firm and its measure of central connectedness in the human capital network for the absolute variable estimation model.

As has been the case for most of this analysis, a predominant cause of the correlation found for equation 10a is a result of the outlier from the data, Merck. Although Exhibit 27 shows Merck's *moderate* position in the human capital movement network in 1994, it had been much higher for the preceding decade and the years of Merck's peak patent output coincide with high values of central connectedness.

One problem that affected the logarithmic models was the high frequency of zero values in the independent variables (Movement_A and Movement_B). The logarithmic model fails to recognize the zero-value observations in the variable transformation from Movement_A to Log(Movement_A). Thus, the two logarithmic models utilized only 21 and 36 observations, respectively. High correlation would hardly be expected with such low movement frequency compounded with spotty data caused by the logarithmic model's omission of zero-value data.

While these results are not extremely supportive of the tacit-knowledge hypotheses, nonetheless, it is the belief of the author that productivity is greatly enhanced by the addition of STAR scientists. Future work detailing internal firm-level productivity measures would be very useful in further investigating this hypothesis. In this case, while the data were not supportive of the hypotheses, they were in no way disproving, either.

The positive correlation between the central connectedness variable and productivity is very encouraging. There exists a building literature suggesting the huge value to be gained by locating oneself or one's firm centrally in the social network. My findings suggest that these networks can be extended to include variables other than just collaborative agreements (Powell, [1996]) and star bio-scientist coauthorship (Zucker, Darby, et. al. [1996a] and [1996b]).

Future areas of study might include human capital movement studies of scientists with publication frequency below that of the studied STAR authors. Also, it would be interesting to apply this central connectedness technique to the semiconductor industry, where the network of human capital movements would be orders-of-magnitude more complex.

V. Conclusion - Human Capital Movement

The positive correlation between the central connectedness variable and productivity is very encouraging. There exists a building literature suggesting the huge value to be gained by

locating the firm centrally in the social network. My findings suggest that these networks can be extended to include variables other than just collaborative agreements (Powell, [1996]) and star bio-scientist coauthorship (Zucker, Darby, et. al. [1996a] and [1996b]).

It does not seem plausible that a firm would adopt the objective of locating itself centrally in the network of human capital movement as a means of enhancing productivity. On the other hand, the pharmaceutical industry can glean valuable lessons from the results presented above. Most importantly, the benefit of being centrally located in an informational network can not be underestimated. Regardless of the channel for this flow of information (human capital movement, publications, collaborative agreements, etc.) the access to information and the internal ability to process it has been shown to be one of the most important capabilities an organization can possess.

Chapter VII – Conclusion

This thesis has contributed to the literature on the subject of human capital quality in the pharmaceutical industry. I have also discussed human capital movement data for the industry as a whole, as well as for the individual firms. The major findings are as follows:

- **Human Capital Quality (as measured by the number of STAR scientists) is positively correlated with research productivity.**

- **Human Capital Quality, measured differently via graduate university ranking, is also positively correlated with research productivity.**

- **The aggregate level of human capital movement among elite scientists in the pharmaceutical industry is surprisingly high, measuring 15-times that found for mangers in the Canadian Biotech Industry. However, these reported levels of inter-firm movements are dwarfed by those found among high-tech industries in microelectronics or semiconductor in the Silicon Valley region.**

- **Firm-level human capital movement data did not show statistically significant correlation with research productivity; however, the measure of a firm's central connectedness in the network of human capital movements did show positive correlation with research productivity.**

Productivity's link to the number of STAR authors has far-reaching effects in the area of hiring and employee retention issues. If an excessive share of the research productivity of an organization falls on the shoulders of a few key scientists, perhaps the recruitment of the elite scientists from other firms would be a value-creating endeavor. On the other hand, perhaps a pro-publication culture within a firm would re-focus the research efforts on the exploration of basic science as opposed to strict concentration on the development of

previously identified drug candidates. Scientists have communicated with me that some firms have an internal aversion to publication by their scientists. Managers at some of the sample firms have told STAR scientists that authoring of journal articles should be conducted on "free-time, " or when development work was slow. With STAR authors having been shown highly correlated with patent output, I would tend to question the reasoning behind these corporate practices.

The findings in Chapter IV have implications in numerous areas of corporate policy. They support the recruitment of researchers from the universities with strong academic reputation. Although the use of regression statistics in this manner is tenuous, it could be interpreted that hiring scientist only from tier-one universities rather than the median program would increase productivity by 24 important patents per year, a quite large increase in productivity, to say the least. With human capital playing such a deterministic role, the findings above would seem extremely useful to managers in the pharmaceutical industry.

Finally, he positive correlation between the central connectedness variable and productivity is very encouraging. Although it does not seem plausible that a firm would adopt the objective of locating itself centrally in the network of human capital movement as a means of enhancing productivity, knowledge of the effects of positioning in the human capital network is very valuable. Most importantly, the benefit of being centrally located in an informational network can not be underestimated. Regardless of the channel for this flow of information (human capital movement, publications, collaborative agreements, etc.) the access to information and the internal ability to process it has been shown to be one of the most important capabilities an organization can possess.

In all, human capital's effect on research productivity is a key issue for managers in the pharmaceutical industry. The findings presented here represent valuable information that can be used in the formulation of their corporation's strategic policy.

WORKS CITED

Angel, D. P., 1989, 'The Labor-Market for Engineers in the United-States Semiconductor Industry', *Economic Geography*, 65(2), pp. 99-112.

Arora, A., and Gambardella, A., 1990, 'Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology', *Journal of Industrial Economics*, 38(4), pp. 361-379.

Arora, A., and Gambardella, A., 1994, 'Evaluating Technological Information and Utilizing It – Scientific Knowledge, Technological Capability, and External Linkages in Biotechnology', *Journal of Economic Behavior & Organization*, 24(1), pp. 91-114.

Arthur, Michael B., 1994, 'The Boundaryless Career: A New Perspective for Organizational Inquiry', *Journal of Organizational Behavior*, 15(4), pp. 295-306.

Arthur, Michael B., Claman, Priscilla H., DeFillippi, Robert J., and Adams, Jerome, 1995 'Intelligent Enterprise, Intelligent Careers', *Academy of Management Executive*, 9(4), pp. 7-22.

Becker, G. S. and Parsons, O. I., 1990, 'Human Capital, Fertility, and Economic-Growth', *Journal of Political Economy*, 98(5), pp. S12-S37.

Berelson, Bernard, 1960, Graduate Education in the United States, New York: McGraw-Hill Book Company, 346p.

Bolland, J. M., 1988, 'Sorting Out Centrality – An Analysis of the Performance of 4 Centrality Models in Real and Simulated Network', *Social Networks*, 1(3), pp. 233-252.

Borgatti, S. P., Everett, M. G., and Freeman, L. C., 1992, UCINET IV Version 1.00, Columbia, SC., Analytic Technologies.

Brown, J. S. and Durguid, P., 1991, 'Organizing Knowledge', *California Management Review*, 40(3), p. 90-103.

Burt, R. S., 1997, 'A Note on Social Capital and Network Content', *Social Networks*, 19(4), pp. 355-373.

Cockburn, Iain M., and Henderson, Rebecca M., 1998, 'Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery', *Journal of Industrial Economics*, 46(2), pp. 157-182.

Davies, B. R., and Lazniarz, J. M., 1985, 'A Site Selection Model for High Technology Manufacturing Firms in the United States', *Scientometrics*, 8(1-2), pp. 103-116.

DeBresson, Chris, and Amesse, Fernand, 1991, 'Networks of Innovators: A Review and Introduction to the Issue', *Research Policy*, 20(5), pp. 363-379.

DeFillippi, Robert J., and Arthur, Michael B., 1994, 'The Boundaryless Career: A Competency-based Perspective', *Journal of Organizational Behavior*, 15(4), pp. 307-324.

Ernst, H., 1998, 'Industrial Research as a Source of Important Patents', *Research Policy*, 27(1), pp. 1-15.

Gabe, Larry, and Goldberg, Michele, 'Protecting Human Capital', *Pharmaceutical Executive*, 19(11), pp. 67-72.

Galaskiewicz, J. 1991, 'Estimating Point Centrality using Different Network Sampling Techniques', *Social Networks*, 13(4), pp. 347-386.

Gambardella, Alfonso, 1992, 'Competitive Advantages from In-House Scientific Research: The US Pharmaceutical Industry in the 1980s', *Research Policy*, 21(5), pp. 391-407.

Garfield, E., 1985, 'Uses and Misuses of Citation Frequency', *Current Contents*, 39(43), pp. 3-9.

Griliches, Z., 1994, 'Productivity, R&D, and the Data Constraint', *American Economic Review*, 84(1), pp. 1-23.

Gunz, Hugh P., 1990, 'Careers and the Corporate Climbing Frame', *Leadership & Organization Development Journal*, 11(2), pp. 17-24.

Gunz, Hugh P., Evans, Michael G., and Jalland, R. Michael, 1999, 'Career Boundaries in a 'Boundaryless' World', To appear in Conversations in Career Theory, Ed. M.A. Peiperl and M.B. Arthur, Oxford: Oxford University Press.

Gunz, Hugh P., and Jalland, R. Michael, 1996, 'Managerial Careers and Business Strategies', *Academy of Management Review*, 21(3), pp. 718-756.

Hargens, L., and Schuman, H., 1990, 'Citation Counts and Social Comparisons – Scientist Use and Evaluation of Citation Index Data', *Social Science Research*, 19(3), pp. 205-221.

Henderson, Rebecca M., and Cockburn, Iain M., 1994, 'Measuring Competence? Exploring Firm Effects in Pharmaceutical Research', *Strategic Management Journal*, 15, pp. 63-84.

Henderson, Rebecca M., and Cockburn, Iain M., 1996, 'Scale, Scope and Spillovers: The Determinants of Research Productivity in Drug Discovery', *RAND Journal of Economics*, 27(1), pp. 32-59.

Hisrich, K. G., 1975, 'Research Spending in the Microelectronics Industry', *Investment Banking*, 3(3), pp. 22-29.

Ingoglia, Marc, and Kline, Amy, 1998, 'Scale Operations in the Northeastern US Overnight Shipping Industry', *Journal of Logistics*, 3(1), pp. 22-41.

Jones, Lyle V., and Coggeshall, Porter E. Eds., 1982a, *An Assessment of Research-Doctorate Programs in the United States: Biological Sciences*, National Research Council, Washington: National Academy Press, 251p.

Jones, Lyle V., and Coggeshall, Porter E. Eds., 1982b, *An Assessment of Research-Doctorate Programs in the United States: Mathematical & Physical Sciences*, National Research Council, Washington: National Academy Press, 243p.

Jones, Lyle V., and Coggeshall, Porter E. Eds., 1982c, *An Assessment of Research-Doctorate Programs in the United States: Social & Behavioral Sciences*, National Research Council, Washington: National Academy Press, 249p.

Kong, S. X., Wertheimer, A. I., Serradell, J, and McGhan, W. F., 1994, 'Psychometric Evaluation of Measures of Organizational Commitment and Intention to Quit Among Pharmaceutical Scientists', *Pharmaceutical Research*, 11(1), pp. 171-180.

Mandler, David, 1993, 'Landscape Architecture Productivity Enhancements in the Old Farms Region of Western Pennsylvania', *International Labor Review*, 31(1), pp. 22-31.

Maxwell, Robert A., and Eckhardt, Shohren B., 1990, Drug Discovery: A Casebook and Analysis, Clifton: Humana Press, 438p.

Nelson, Richard R., 1990a, 'U.S. Technological Leadership: Where Did It Come From, and Where Did It Go?', *Research Policy*, 19(1), pp. 119-132.

Nelson, Richard R., 1990b, 'Capitalism as an Engine of Progress', *Research Policy*, 19(1), pp. 193-214.

Powell, Walter W., Koput, Kenneth W., and Smith-Doerr, Laurel, 1996, 'Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology', *Administrative Science Quarterly*, 41(1), pp. 116-146.

Rogers, Everett M., 1984, Silicon Valley Fever: Growth of High-Technology Culture, New York: Basic Books, 302 p.

Samuel, C., 1998, 'The Investment Decision: a Re-examination of Competing Theories Using Panel Data', *Applied Economics*, 30(1), pp. 95-104.

Saxenian, Annalee, 1990, 'Regional Networks and the Resurgence of Silicon Valley', *California Management Review*, 33(1), pp. 89-112.

Saxenian, Annalee, 1991, 'The Origins and Dynamics of Production Networks in Silicon Valley', *Research Policy*, 20(5), pp. 423-437.

Saxenian, Annalee, 1994a, 'Silicon Valley versus Route 128', *Inc.*, 16(2), pp. 25-26.

Saxenian, Annalee, 1994b, 'Lessons from Silicon Valley', *Technology Review*, 97(5), pp. 42-51.

Scott, A. J., 1987, 'The United-States Semiconductor Industry – A Locational Analysis', *Environment and Planning A*, 19(7), pp. 875-912.

Stevenson, K., and Zelen, M., 1989, 'Rethinking Centrality – Methods and Examples', *Social Networks*, 11(1), pp. 1-37.

Stinchcombe, Arthur, 1990, Information and Organization, Berkeley: University of California Press, 391 p.

Stohr, W. B., 1986, 'Regional Innovation Complexes', *Papers of the Regional Science Association*, v. 59, pp. 29-44.

Storper, M., and Christopherson, S., 1987, 'Flexible Specialization and Regional Agglomerations – The Case of the United-States Motion-Picture Industry', *Annals of the Association of American Geographers*, 77(1), pp. 104-107.

Storper, M., and Scott, AJ, 1990, 'Work Organization and Local-Labor Markets in an Era of Flexible Production', *International Labor Review*, 129(5), pp. 573-591.

Valente, T. W., and Foreman, R. K., 1998, 'Integration and Radiality: Measuring the Extent of an Individual's Connnectedness and Reachability in a Network', *Social Networks*, 20(1), pp. 89-105.

Zucker, L. G., and Darby, M. R., 1995, 'Virtuous Circles of Productivity: Star Bioscientists and the Institutional Transformation of Industry', *National Bureau of Economic Research Working Paper* 5342, 51 p

Zucker, L. G., and Darby, M. R., 1996a, 'Costly Information – Firm Transformation, Exit, or Persistent Failure', *American Behavioral Scientist*, 39(8), pp. 959-974.

Zucker, L. G., and Darby, M. R., 1996b, 'Star Scientists and Institutional Transformation: Patterns of Invention and Innovation in the Formation of the Biotechnology Industry', *Proceedings of the National Academy of Sciences of the United States of America*, 93(23), pp. 12709-12716.

Zucker, L. G., Darby, M. R., and Armstrong, J., 1994, 'Intellectual Capital and the Firm, The Technology of Geographically Localized Knowledge Spillovers', *National Bureau of Economic Research Working Paper* 4946, 61 p.

Zucker, L. G., Darby, M. R., and Armstrong, J. 1998, 'Geographically Localized Knowledge: Spillovers or Markets?', *Economic Inquiry*, 36(1), pp. 65-86.

Zucker, L. G., Darby, M. R., and Brewer, M. B., 1998, 'Intellectual Human Capital and the Birth of the US Biotechnology Enterprises', *American Economic Review*, 88(1), pp. 290-306.

APPENDIX A

Exhibits 1-30

Firm	Variable Name	Location	Merger
Abbott Laboratories	ABBOTT	USA	
Beecham Pharmaceuticals	BEECHAM	USA	Yes
Bristol-Myers Squibb Company	B-M-S	USA	Yes
Bristol-Myers	BRISTOL-MYERS	USA	Yes
Burrows Wellcome	B-W	UK	Yes
Ciba-Geigy, AG.	CIBA-GEIGY	Switz.	
Fujisawa Healthcare, Inc.	FUJISAWA	Japan	
Glaxo Ltd.	GLAXO	UK	Yes
Hoechst Marion	HOECHST	Germany	
Hoffman La Roche	HOFFMAN	Germany	
Eli Lilly & Company	LILLY	USA	
Merck & Co., Inc.	MERCK	USA	
Norwich Eaton Pharmaceuticals	NORWICH	Eur.	Yes
Procter and Gamble - Pharmacia	P&G PHARMA	USA	Yes
Pfizer Incorporated	PFIZER	USA	
Sankyo Seiki Mfg. Co., Ltd.	SANKYO	Japan	
G.D. Searle Company	SEARLE	USA	
Smithkline Beecham	S-K-B	USA	Yes
Smithkline	SMITHKLINE	USA	Yes
Squibb Pharmaceuticals	SQUIBB	USA	Yes
Takeda Chemical Industries, LTD.	TAKEDA	Japan	
Pharmacia & Upjohn	UPJOHN	USA	
Yamanouchi Pharmaceuticals	YAMANOUCHI	Japan	

EXHIBIT 1 - Pharmaceutical Firm Sample - Complete List

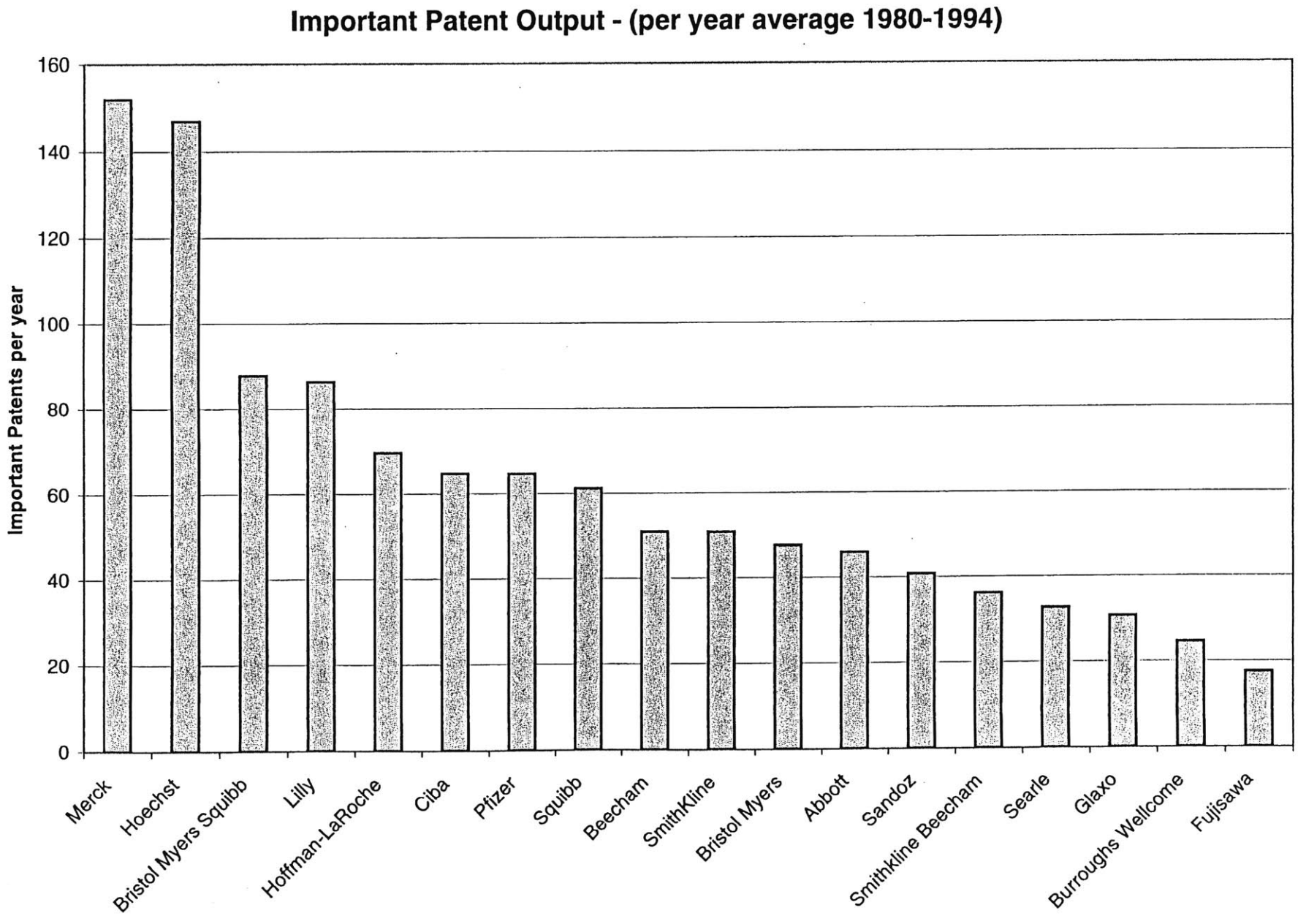


Exhibit 2 - Important Patent Output by Firm

Firm	Total Authors	Total Papers
ABBOTT	2329	12268
B-W	2315	12195
MERCK	4786	25211
SEARLE	889	4683
HOFFMAN	2065	10878
NORWICH	191	1006
BRISTOL-MYERS	745	3924
SQUIBB	624	3287
SMITHKLINE	714	3761
BEECHAM	279	1470
S-K-B	2218	11684
GLAXO	2081	10962
LILLY	2469	13006
PFIZER	1783	9392
UPJOHN	2151	11331
CIBA-GEIGY	3921	20654
FUJISAWA	675	3556
HOECHST	1802	9492
SANKYO	736	3877
TAKEDA	862	4541
YAMANOUCHI	444	2339
P&G PHARMA	61	321
B-M-S	2174	11452
	36314	191288

Exhibit 3 - Total Author and Paper Count for Sample Firms

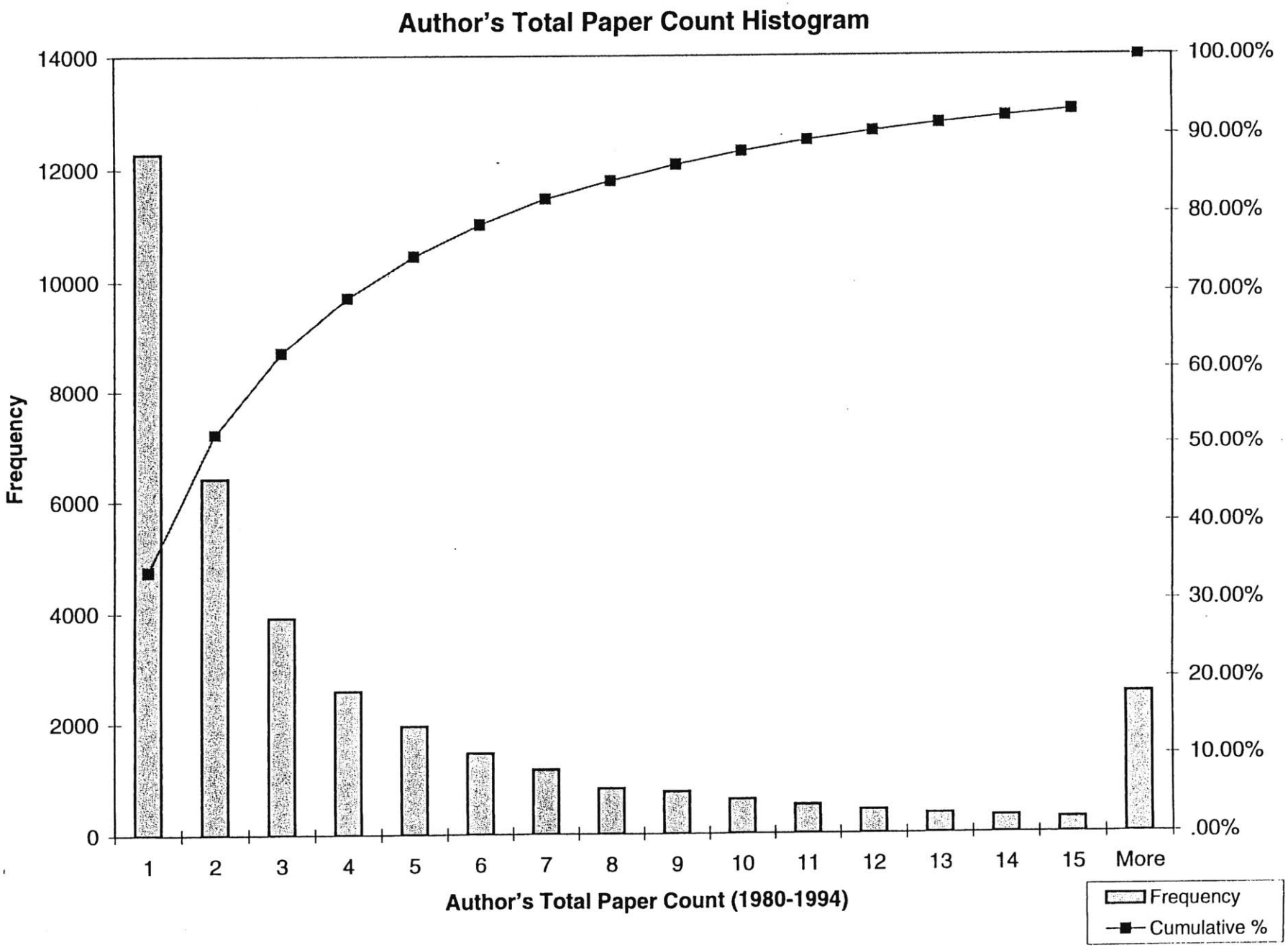


Exhibit 4 - Career Publication Frequency Histogram

Total Stars Per Firm

year of first publication

	80-84	85-89	90-94	sum
MERCK	54	66	55	175
S-K-B	0	0	67	67
ABBOTT	5	22	37	64
B-W	46	17	-1	62
UPJOHN	24	17	18	59
CIBA-GEIGY	27	15	13	55
GLAXO	18	3	23	44
LILLY	21	10	12	43
B-M-S	0	0	36	36
HOFFMAN	15	14	-2	27
PFIZER	5	2	10	17
HOECHST	12	4	0	16
FUJISAWA	11	5	-1	15
TAKEDA	16	1	-2	15
SMITHKLINE	4	3		7
BEECHAM	2	3		5
SEARLE	0	2	2	4
SANKYO	4	1	-1	4
YAMANOUCHI	2	2	-1	3
BRISTOL-MYERS	3	-1		2
SQUIBB	2	0		2
NORWICH	0	0	0	0
P&G PHARMA	0	0	0	0

Exhibit 5 - Total Stars per Firm (*see Exhibit 9 for graphical representation*)

STAR1 Scientists per Firm (1980-1994)

	YEAR														
	80	**81**	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**	**91**	**92**	**93**	**94**
ABBOTT	4	8	12	15	14	23	28	35	40	37	44	53	53	52	51
MERCK	43	51	61	74	79	91	103	114	124	122	131	142	144	146	140
SEARLE					1	2	2	2	1	2	3	4	4	4	4
HOFFMAN	7	10	14	17	16	19	21	22	22	16	18	22	22	20	19
LILLY	20	22	23	27	27	29	34	34	39	39	43	44	46	44	40
PFIZER	5	7	7	8	8	7	9	10	9	13	14	15	14	15	15
CIBA-GEIGY	25	29	33	34	35	39	43	45	47	49	53	54	53	52	52
FUJISAWA	9	11	12	10	10	14	16	15	15	16	16	16	16	14	14
HOECHST	11	13	14	16	16	15	17	19	19	17	17	15	17	17	15
SANKYO	4	5	4	4	5	5	5	5	5	5	5	4	4	4	4
TAKEDA	13	13	14	15	16	14	17	15	15	17	17	15	14	13	13
UPJOHN	23	25	29	31	33	38	44	47	51	52	53	54	58	55	52
YAMANOUCHI	2	2	3	4	4	4	4	3	3	2	2	3	2	2	3
B-W	38	44	44	47	53	53	53	61	60	58	59	56	55	53	52
GLAXO	14	17	18	18	18	17	21	23	24	31	31	35	39	40	40
NORWICH															
P&G PHARMA															
BRISTOL-MYERS	3	3	3	3	2	2	2	1	1	1					
SQUIBB	2	2	2	2	2	2	2	2	2	1					
B-M-S											9	17	24	25	25
SMITHKLINE															
BEECHAM															
S-K-B											34	42	45	46	46

Exhibit 6 - STAR1 Scientists per Firm

STAR2 Scientist per Firm (1980-1994)

	YEAR														
	80	**81**	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**	**91**	**92**	**93**	**94**
ABBOTT	1	1	1	3	3	3	6	7	7	7	9	9	9	9	9
MERCK	6	7	10	12	16	18	19	20	21	22	23	24	23	23	23
SEARLE															
HOFFMAN	4	4	4	4	4	5	5	5	4	4	5	4	4	3	3
LILLY	1	1	2	2	2	2	2	3	3	3	3	3	3	3	3
PFIZER			1	1	1		1	1	1	1	1	2	2	2	2
CIBA-GEIGY	2	3	3	3	3	3	3	3	4	4	4	4	4	4	3
FUJISAWA	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1
HOECHST	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
SANKYO															
TAKEDA	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2
UPJOHN	1	2	2	2	2	3	4	5	7	7	7	7	7	7	7
YAMANOUCHI															
B-W	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5
GLAXO	2	2	2	2	2	2	2	1	2	3	3	3	3	3	3
NORWICH															
P&G PHARMA															
BRISTOL-MYERS															
SQUIBB															
B-M-S											5	6	6	6	6
SMITHKLINE															
BEECHAM															
S-K-B											4	4	4	4	4

Exhibit 7 - STAR2 Scientists per Firm

STAR3 Scientist per Firm (1980-1994)

	YEAR														
	80	**81**	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**	**91**	**92**	**93**	**94**
ABBOTT						1	1	1	1	3	4	4	4	4	4
MERCK	5	5	6	6	10	11	12	13	13	13	13	13	13	13	12
SEARLE															
HOFFMAN	4	4	4	4	4	5	5	5	4	4	5	5	5	5	5
LILLY															
PFIZER															
CIBA-GEIGY															
FUJISAWA															
HOECHST															
SANKYO															
TAKEDA															
UPJOHN															
YAMANOUCHI															
B-W	4	4	4	4	5	5	5	5	5	5	5	5	5	5	5
GLAXO	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1
NORWICH															
P&G PHARMA															
BRISTOL-MYERS															
SQUIBB															
B-M-S											1	5	5	5	5
SMITHKLINE															
BEECHAM															
S-K-B											4	4	4	4	4

Exhibit 8 - STAR3 Scientist per Firm

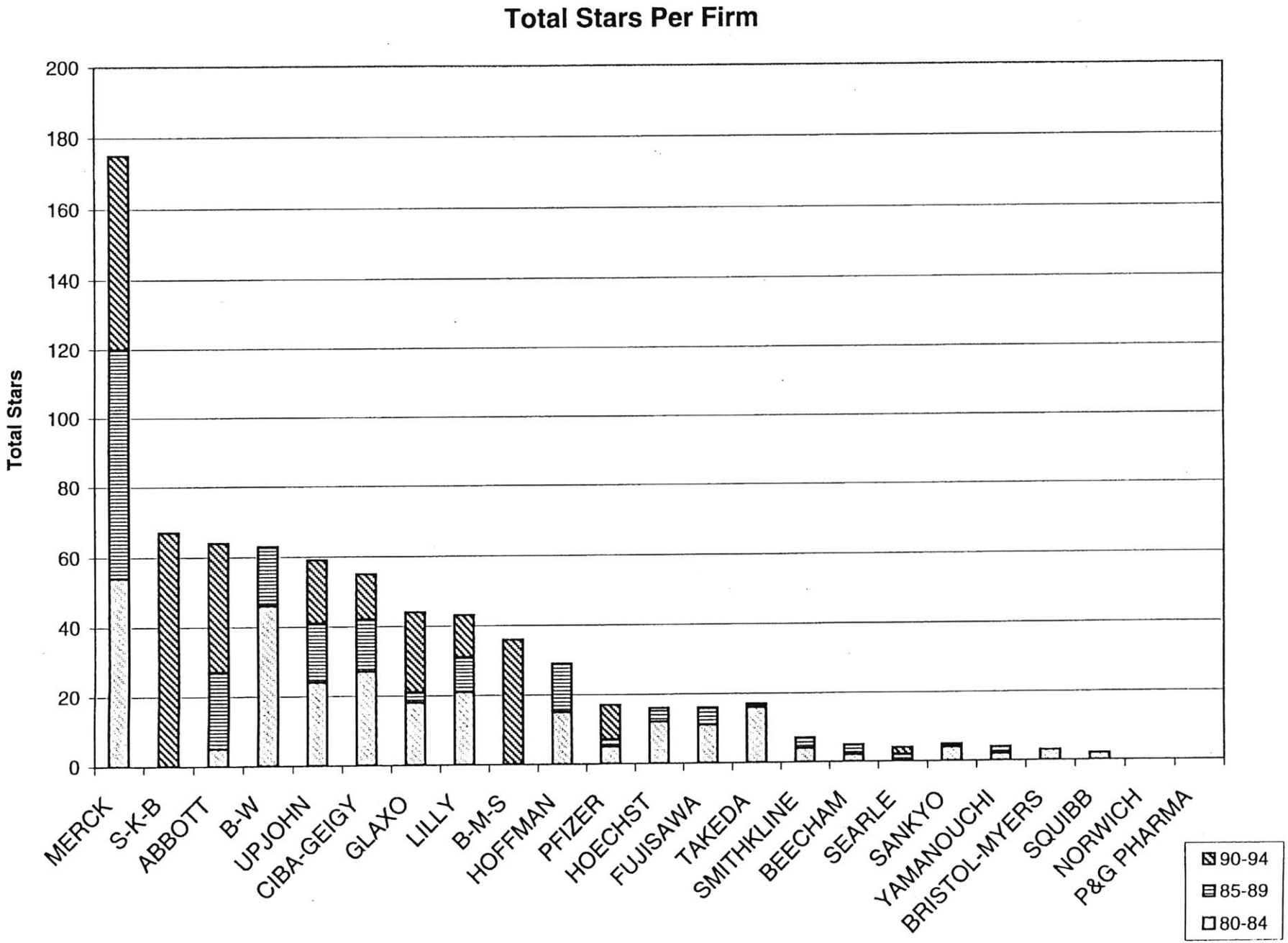


Exhibit 9 - Total STAR Author per Frim (year of first publication)

Firm	Variable Name	Location	Regression
Included			
Abbott Laboratories	ABBOTT	USA	Yes
Beecham Pharmaceuticals	BEECHAM	USA	Yes
Bristol-Myers Squibb Company	B-M-S	USA	Yes
Bristol-Myers	BRISTOL-MYERS	USA	Yes
Burrows Wellcome	B-W	UK	Yes
Ciba-Geigy, AG.	CIBA-GEIGY	Switzerland	Yes
Fujisawa Healthcare, Inc.	FUJISAWA	Japan	Yes
Glaxo Ltd.	GLAXO	UK	Yes
Hoechst Marion	HOECHST	Germany	Yes
Hoffman La Roche	HOFFMAN	Germany	Yes
Eli Lilly & Company	LILLY	USA	Yes
Merck & Co., Inc.	MERCK	USA	Yes
Pfizer Incorporated	PFIZER	USA	Yes
G.D. Searle Company	SEARLE	USA	Yes
Smithkline Beecham	S-K-B	USA	Yes
Smithkline	SMITHKLINE	USA	Yes
Squibb Pharmaceuticals	SQUIBB	USA	Yes
Not Included			
Takeda Chemical Industries, LTD.	TAKEDA	Japan	NO
Pharmacia & Upjohn	UPJOHN	USA	NO
Yamanouchi Pharmaceuticals	YAMANOUCHI	Japan	NO
Norwich Eaton Pharmaceuticals	NORWICH		NO
Procter and Gamble - Pharmacia	P&G PHARMA	USA	NO
Sankyo Seiki Mfg. Co., Ltd.	SANKYO	Japan	NO

EXHIBIT 10 - Pharmaceutical Firm Sample - Firms Included in Regression Analysis

CORRELATION MATRIX

	AUCOUNT	SALES	STAR1	STAR2	STAR3	TOT_STAR	ADJ_HUM_CAP	Movement_A	Movement_B	CENTRAL
AUCOUNT	1.00	0.84	0.81	0.79	0.85	0.82	0.36	0.29	0.52	0.61
SALES	0.84	1.00	0.69	0.74	0.69	0.71	0.25	0.34	0.57	0.66
STAR1	0.81	0.69	1.00	0.94	0.85	1.00	0.46	0.20	0.34	0.49
STAR2	0.79	0.74	0.94	1.00	0.89	0.96	0.44	0.22	0.36	0.52
STAR3	0.85	0.69	0.85	0.89	1.00	0.88	0.33	0.17	0.34	0.46
TOT_STAR	0.82	0.71	1.00	0.96	0.88	1.00	0.46	0.21	0.35	0.50
ADJ_HUM_CAP	0.36	0.25	0.46	0.44	0.33	0.46	1.00	-0.05	-0.01	0.09
Movement_A	0.61	0.66	0.49	0.52	0.46	0.50	0.09	0.57	0.91	1.00
Movement_B	0.52	0.57	0.34	0.36	0.34	0.35	-0.01	0.65	1.00	0.91
CENTRAL	0.29	0.34	0.20	0.22	0.17	0.21	-0.05	1.00	0.65	0.57

COVARIANCE MATRIX

	AUCOUNT	SALES	STAR1	STAR2	STAR3	TOT_STAR	ADJ_HUM_CAP	Movement_A	Movement_B	CENTRAL
AUCOUNT	4.E+05	1.E+09	2.E+04	3.E+03	2.E+03	2.E+04	20.06	144.53	540.58	8.E+02
SALES	1.E+09	6.E+12	5.E+07	9.E+06	5.E+06	7.E+07	5.E+04	6.E+05	2.E+06	3.E+06
STAR1	2.E+04	5.E+07	964	150	84	1198	1.23	4.92	17.14	31
STAR2	3.E+03	9.E+06	150	26	14	191	0.19	0.86	2.94	5
STAR3	2.E+03	5.E+06	84	14	10	109	0.09	0.43	1.73	3
TOT_STAR	2.E+04	7.E+07	1198	191	109	1498	1.51	6.20	21.81	39
ADJ_HUM_CAP	2.E+01	5.E+04	1	0	0	2	0.01	0.00	0.00	0
Movement_A	8.E+02	3.E+06	31	5	3	39	0.02	0.89	2.96	4
Movement_B	5.E+02	2.E+06	17	3	2	22	0.00	0.81	2.58	3
CENTRAL	1.E+02	6.E+05	5	1	0	6	0.00	0.60	0.81	1

DESCRIPTIVE STATISTICS

	AUCOUNT	SALES	STARS1	STARS2	STARS3	STARS_TOT	ADJ_HUM_CAP	MOVEMENT_A	MOVEMENT_B	CENTRAL
MEAN	817	2968937	27	3	2	32	2	0	1	1
MEDIAN	658	2241500	17	2	0	22	2	0	0	0
MAX	3206	14969800	146	24	13	182	2	4	9	12
MINIMUM	47	262000	0	0	0	0	1	0	0	0
STD DEV.	629	2253747	29	5	3	37	0	1	2	2
SKEWNESS	1.1	2.4	2.0	2.8	2.0	2.2	-1.5	3.2	2.9	2.8
KURTOSIS	4.0	10.7	7.7	10.9	7.0	8.6	4.5	14.5	12.5	12.4
JARQUE-BERA	53	367	324	789	272	430	99	1467	1046	1015
PROB.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OBSERVATIONS	204	106	204	204	204	204	203	203	203	203

EXHIBIT 11 - Detailed Statistics - w /Correlation and Covariance Matrices for Independent Variables Used in Regressions

Variable	1984		1989		1994	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Star Authors						
Star 1	14.7	19.8	20.8	29.0	21.7	28.6
Star 2	1.9	3.4	2.7	4.8	2.7	4.6
Star 3	0.9	2.4	1.2	2.9	1.3	2.9
Total Stars	18.0	24.6	25.3	35.7	30.7	39.7
Firm Human Capital						
Sample	2.0	0.8	2.1	0.8	2.2	0.8
Adjusted	2.1	0.2	2.2	0.2	2.2	0.3
Star Intensity						
Stars per 1000 authors	6.5	5.8	10.7	8.1	14.9	10.3
Stars per $1B Pharmaceutical Sales	2.4	3.9	4.0	5.2	5.5	6.5
Human Capital Movement						
Inter-firm Switches	0.2	0.4	0.7	1.4	2.1	2.4
Inter-firm Switches per 1000 firm authors (1980-1994)					1.5	1.6
Inter-firm Switches per $1B Pharm. Sales (1980-1994)					0.6	0.7
Normalized Central Connectivity	0.04	0.11	0.04	0.09	0.04	0.06

Exhibit 12 - General Descriptive Statistics for Constructed Variables

Drivers of Research Productivity
(as measured by Important Patent Output)

	Important Patents (t-stats)									
EQUATION	1a	2a	3a	4a	5a	6a	7a	8a	9a	10a
C	54.45 8.59	59.48 11.93	46.50 7.44	53.45 8.70	50.14 7.70	48.18 7.78	-48.07 -1.21	41.24 6.09	39.31 5.83	38.08 5.62
Aucount	-0.05 -2.99	-0.01 -1.39	-0.05 -3.64	-0.04 -3.87	-0.05 -3.73	-0.05 -3.96	-0.02 -1.81	-0.01 -0.84	-0.01 -0.53	0.00 -0.39
Sales	0.00 1.57		8.4E-06 2.88	4.9E-06 1.71	9.5E-06 3.21	8.1E-06 2.79	1.1E-05 3.38	8.6E-06 2.62	1.1E-05 3.18	1.1E-05 3.34
Star1	-0.17 -0.41	-0.05 -0.14	1.02 4.71							
Star2	7.44 2.59	8.34 3.98		7.37 6.10						
Star3	2.03 0.66	-4.74 -2.20			10.31 4.48					
Tot_Star						0.91 5.15				
Adj_Hum_Cap							48.40 2.27			
Movement_A								3.75 0.63		
Movement_B									5.20 1.70	
central										5.81 2.13
R-Squared	0.36	0.23	0.28	0.36	0.36	0.31	0.17	0.13	0.15	0.16
Observations	168	168	106	106	106	168	168	106	106	168

EXHIBIT 13 - ESTIMATION OF IMPORTANT PATENT OUTPUT

Drivers of Research Productivity

(as measured by Important Patent Output)

	LOG(Important Patents) (t-stats)									
EQUATION	1b	2b	3b	4b	5b	6b	7b	8b	9b	10b
C	1.51	10.02	-0.72	-0.15	-2.01	-0.60	-3.10	-9.95	-7.78	-11.55
	0.47	7.00	-0.31	-0.05	-0.61	-0.26	-1.30	-1.38	-1.31	-1.93
L_Aucount	-1.10	-0.94	-0.58	-0.76	-0.99	-0.64	-0.52	-1.21	-1.25	-1.40
	-2.60	-3.82	-2.26	-2.55	-2.38	-2.43	-2.84	-1.52	-2.15	-2.44
L_Sales	0.68		0.54	0.59	0.81	0.55	0.60	1.48	1.34	1.67
	2.34		2.54	2.36	2.57	2.59	3.06	1.85	2.16	2.67
L_Star1	-0.68	-0.72	0.14							
	-2.29	-2.85	1.03							
L_Star2	1.07	1.39		0.30						
	3.42	5.10		1.58						
L_Star3	0.27	0.38			0.44					
	1.00	1.67			1.52					
L_Tot_Star						0.17				
						1.29				
L_Adj_Hum_Cap							2.08			
							2.33			
L_Movement_A								-0.17		
								-0.28		
L_Movement_A									-0.04	
									-0.11	
L_central										-0.35
										-0.97
R-Squared	0.44	0.43	0.21	0.07	0.09	0.07	0.09	0.19	0.16	0.17
	161	75	80	51	161	161	161	21	36	161

EXHIBIT 14 - ESTIMATION OF log(IMPORTANT PATENT OUTPUT)

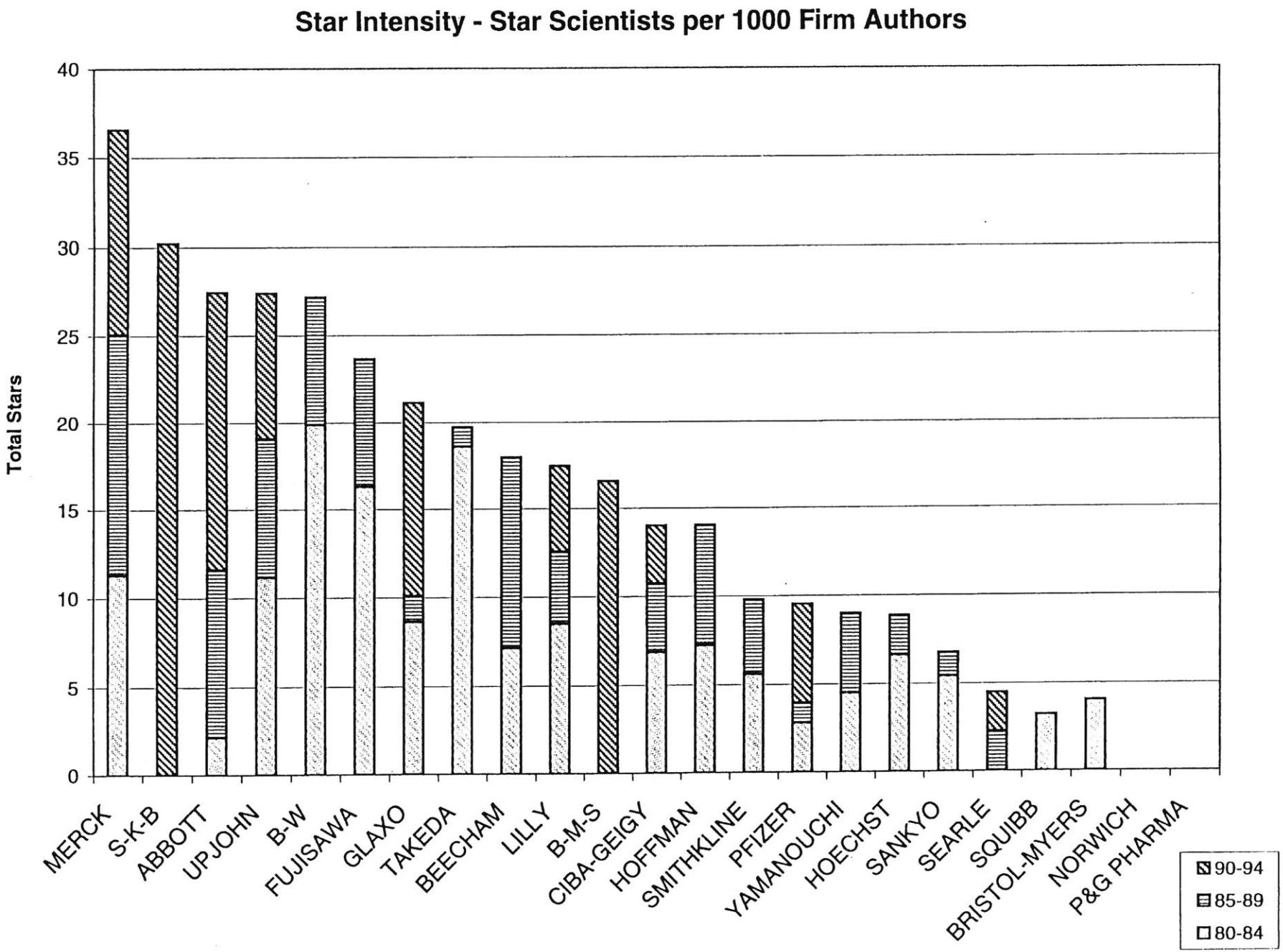


Exhibit 15 - STAR-Intensity (number of STAR scients per 1000 firm authors)

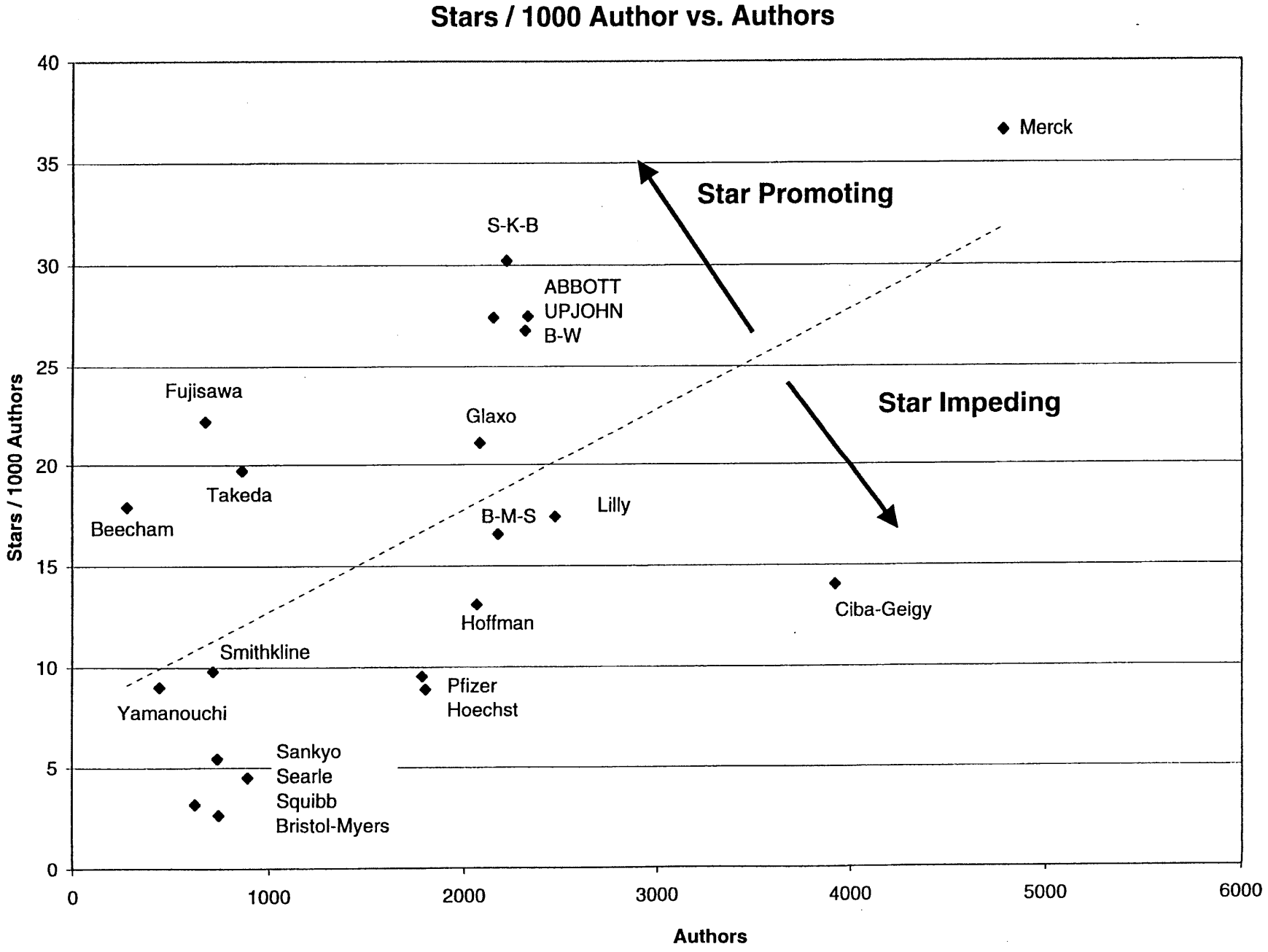


Exhibit 16 - Hypothesized STAR Promoting Impeding

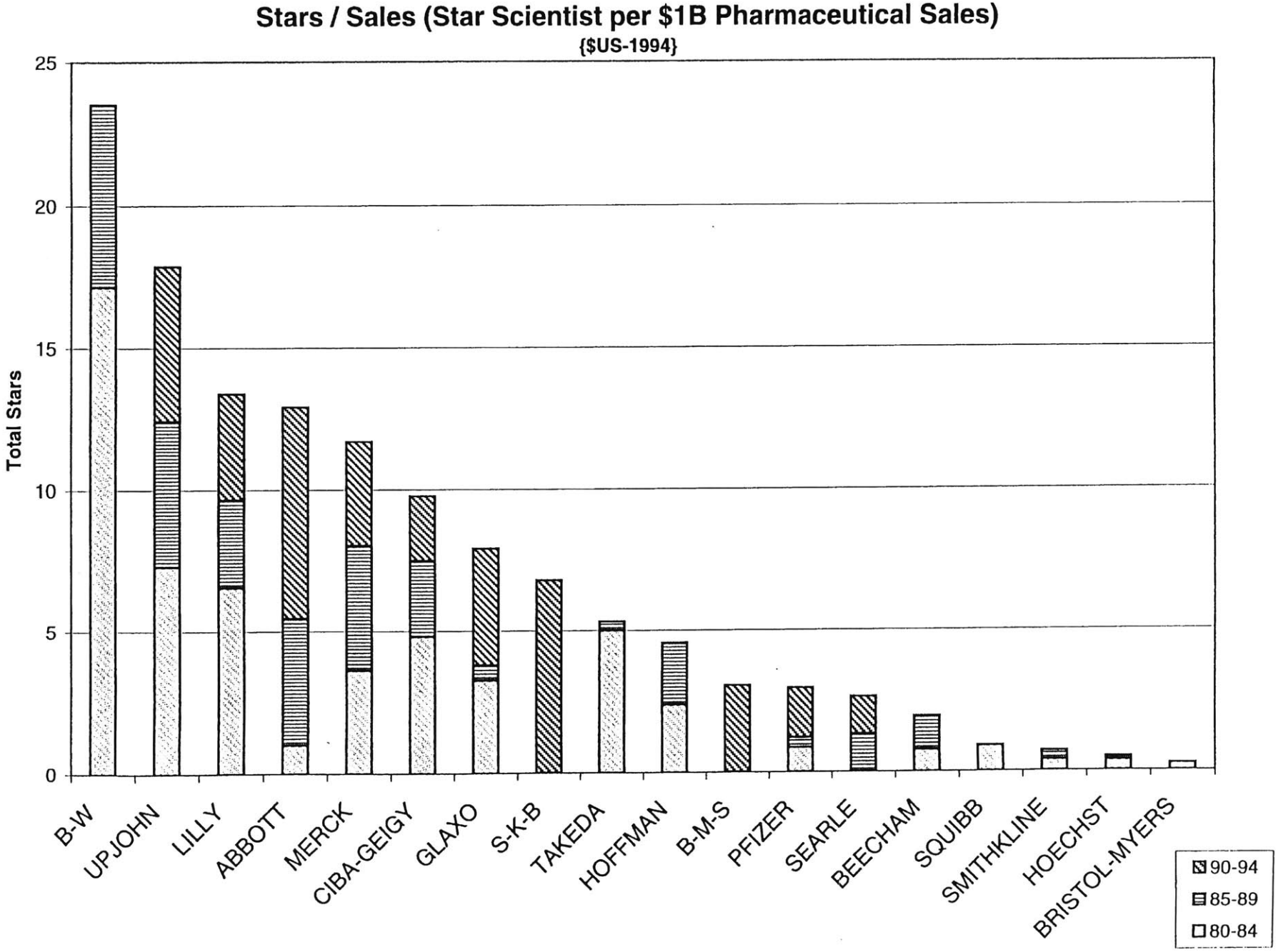


Exhibit 17 - STARS / Sales (STAR Scientists per $1B Pharmaceutical Sales)

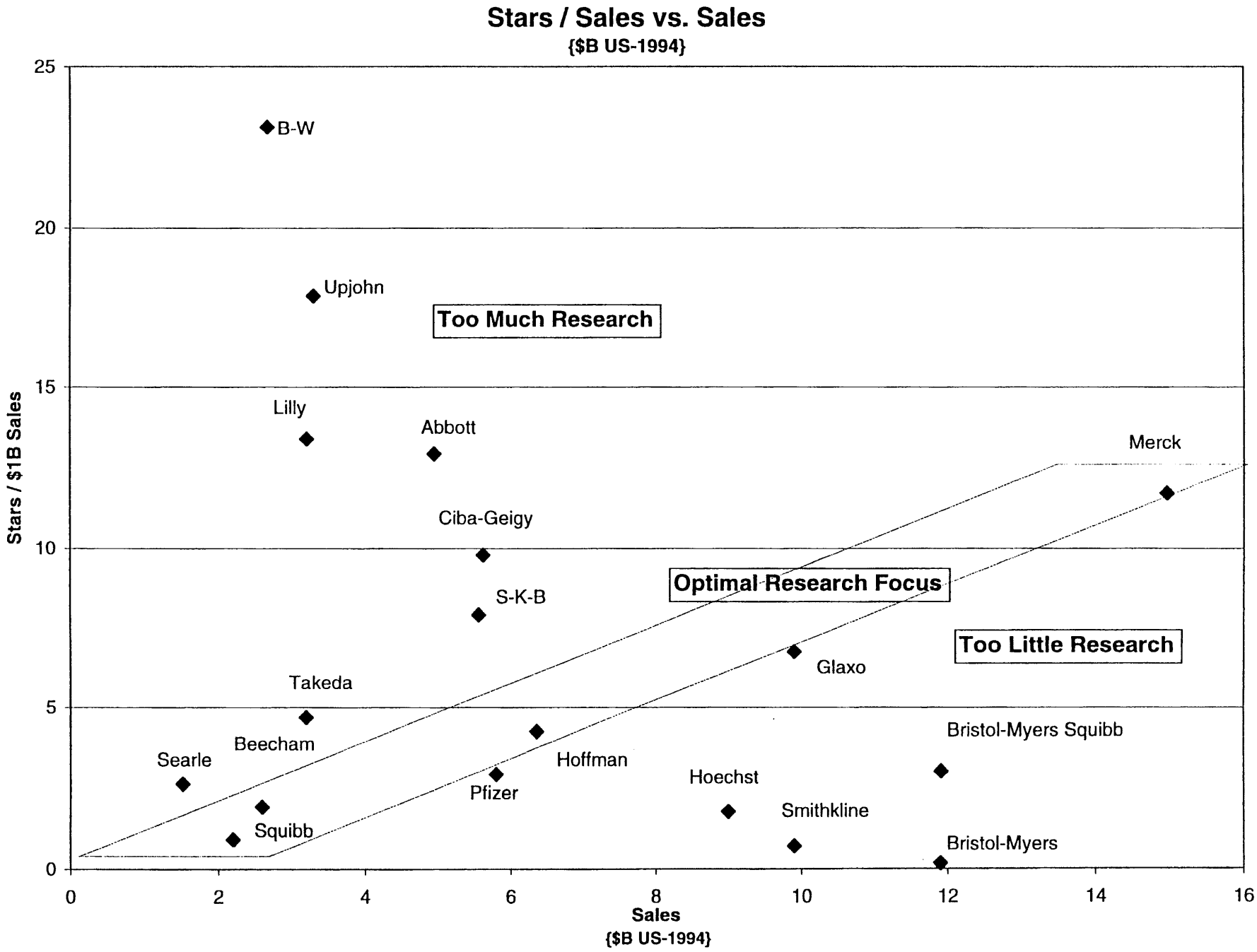


Exhibit 18 - Hypothesized Optimal Research Focus

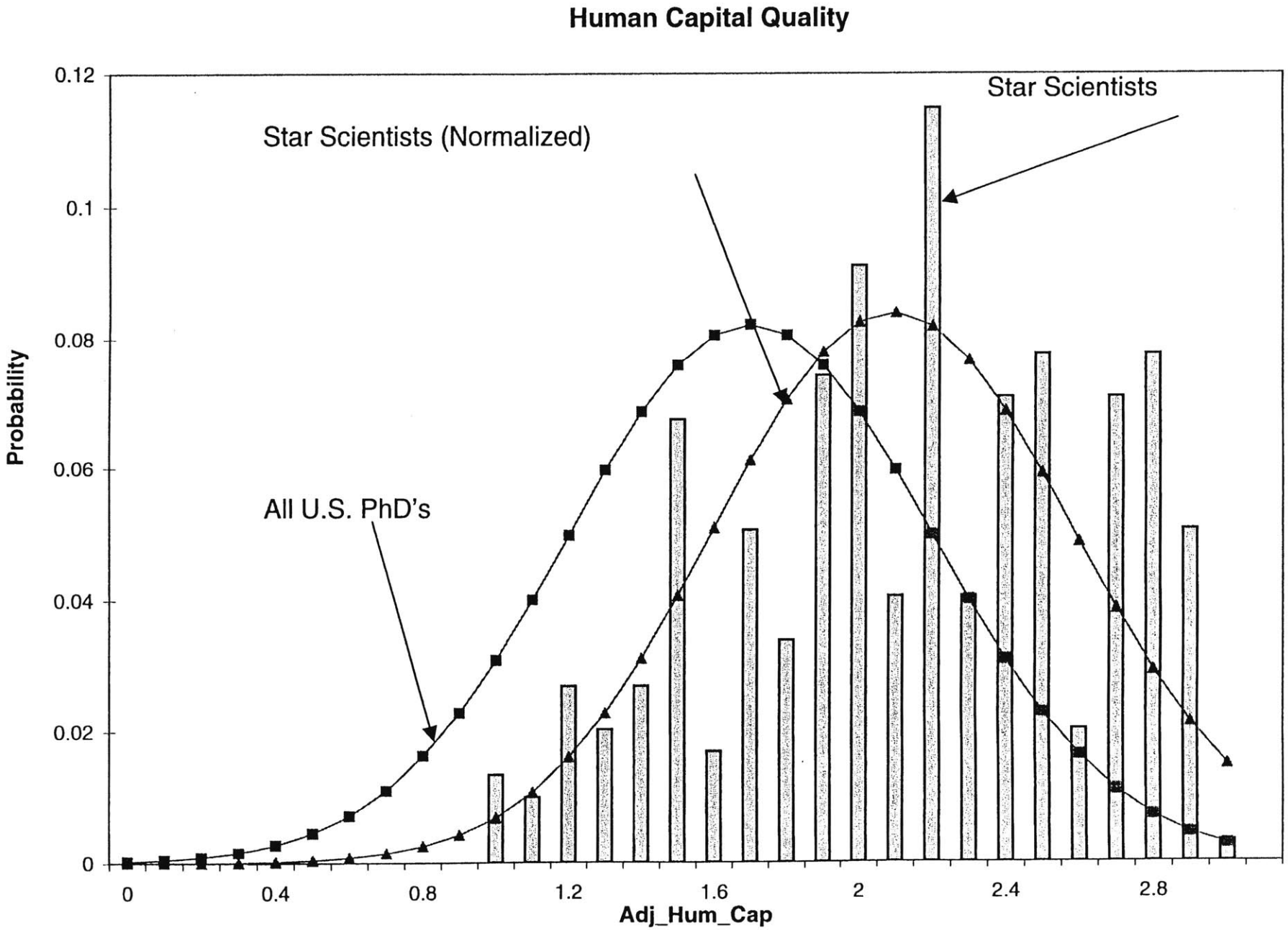


Exhibit 19 - Human Capital Score Histogram (STAR Scientists General Population)

	Augmented Data				Pre-Augmented Data		
FIRM	Total Authors	Sample Size	Adjusted Rank	Stdev	N(extra)	Average (N)	Orig. Rank
ABBOTT	66	36	2.27	0.55			2.27
UPJOHN	67	26	2.16	0.51			2.16
MERCK	203	83	2.16	0.50			2.16
BEECHAM	6	1	2.13	0.00	5	2.18	1.90
LILLY	52	26	2.10	0.46			2.10
CIBA-GEIGY	64	5	2.08	0.25	5	1.98	2.18
TAKEDA	21	2	2.05	0.21			2.05
B-W	87	20	2.05	0.47			2.05
S-K-B	71	25	2.03	0.50			2.03
B-M-S	80	29	2.02	0.45			2.02
SEARLE	4	2	2.00	0.71	8	1.98	2.10
FUJISAWA	20	0	2.00	0.00	2	2.00	0.00
HOFFMAN	38	6	1.98	0.38	4	1.63	2.22
PFIZER	18	8	1.94	0.57	2	2.35	1.84
SQUIBB	20	10	1.89	0.34			1.89
GLAXO	53	6	1.83	0.39	2	1.80	1.83
YAMANOUCHI	4	1	1.80	0.00			1.80
BRISTOL-MYERS	28	7	1.77	0.40	3	1.50	1.89
HOECHST	22	2	1.40	0.42			1.40
SMITHKLINE	10	1	1.30	0.00			1.30
SANKYO	5	0		0.00			0.00
NORWICH	0	0		0.00			0.00
P&G PHARMA	0	0		0.00			0.00

Exhibit 20 - Human Capital Rankings (with Augmented Data)

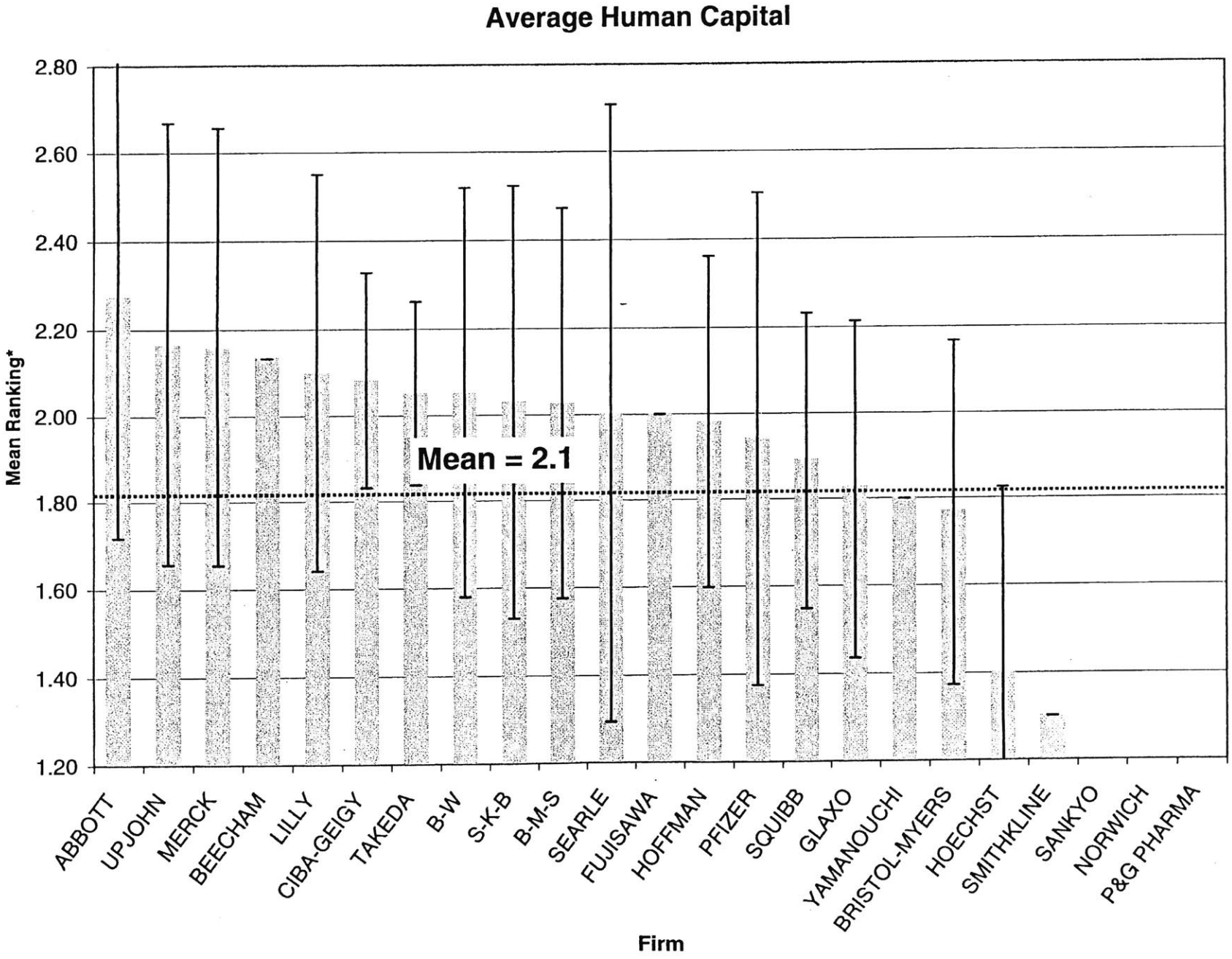


Exhibit 21 - Average Human Capital Score by Firm (Error Bars = one StDev)

Drivers of Research Productivity

(as measured by Important Patent Output)

	Important Patents (t-stats)									
EQUATION	1a	2a	3a	4a	5a	6a	7a	8a	9a	10a
C	54.45	59.48	46.50	53.45	50.14	48.18	-48.07	41.24	39.31	38.08
	8.59	11.93	7.44	8.70	7.70	7.78	-1.21	6.09	5.83	5.62
Aucount	-0.05	-0.01	-0.05	-0.04	-0.05	-0.05	-0.02	-0.01	-0.01	0.00
	-2.99	-1.39	-3.64	-3.87	-3.73	-3.96	-1.81	-0.84	-0.53	-0.39
Sales	0.00		8.4E-06	4.9E-06	9.5E-06	8.1E-06	1.1E-05	8.6E-06	1.1E-05	1.1E-05
	1.57		2.88	1.71	3.21	2.79	3.38	2.62	3.18	3.34
Star1	-0.17	-0.05	1.02							
	-0.41	-0.14	4.71							
Star2	7.44	8.34		7.37						
	2.59	3.98		6.10						
Star3	2.03	-4.74			10.31					
	0.66	-2.20			4.48					
Tot_Star						0.91				
						5.15				
Adj_Hum_Cap							48.40			
							2.27			
Movement_A								3.75		
								0.63		
Movement_B									5.20	
									1.70	
central										5.81
										2.13
R-Squared	0.36	0.23	0.28	0.36	0.36	0.31	0.17	0.13	0.15	0.16
Observations	168	168	106	106	106	168	168	106	106	168

EXHIBIT 22 - ESTIMATION OF IMPORTANT PATENT OUTPUT - Human Capital Quality Models

Drivers of Research Productivity
(as measured by Important Patent Output)

	LOG(Important Patents) (t-stats)									
EQUATION	1b	2b	3b	4b	5b	6b	7b	8b	9b	10b
C	1.51	10.02	-0.72	-0.15	-2.01	-0.60	-3.10	-9.95	-7.78	-11.55
	0.47	7.00	-0.31	-0.05	-0.61	-0.26	-1.30	-1.38	-1.31	-1.93
L_Aucount	-1.10	-0.94	-0.58	-0.76	-0.99	-0.64	-0.52	-1.21	-1.25	-1.40
	-2.60	-3.82	-2.26	-2.55	-2.38	-2.43	-2.84	-1.52	-2.15	-2.44
L_Sales	0.68		0.54	0.59	0.81	0.55	0.60	1.48	1.34	1.67
	2.34		2.54	2.36	2.57	2.59	3.06	1.85	2.16	2.67
L_Star1	-0.68	-0.72	0.14							
	-2.29	-2.85	1.03							
L_Star2	1.07	1.39		0.30						
	3.42	5.10		1.58						
L_Star3	0.27	0.38			0.44					
	1.00	1.67			1.52					
L_Tot_Star						0.17				
						1.29				
L_Adj_Hum_Cap							2.08			
							2.33			
L_Movement_A								-0.17		
								-0.28		
L_Movement_A									-0.04	
									-0.11	
L_central										-0.35
										-0.97
R-Squared	0.44	0.43	0.21	0.07	0.09	0.07	0.09	0.19	0.16	0.17
	161	75	80	51	161	161	161	21	36	161

EXHIBIT 23 - ESTIMATION OF log(IMPORTANT PATENT OUTPUT) - Human Capital Quality Models

Pharmaceutical Industry Scientists

Time Elapsed	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Totals
Total From No-Switch	0	5	32	68	97	41	55	64	72	60	45	47	63	78	179	906
Total From 1-Switch	0	0	0	1	2	2	5	4	4	4	6	4	1	10	12	55
Total from Multi, with mergers	0	0	0	0	1	0	0	1	0	0	0	2	2	1	1	8
Total (1-switch)	0	0	0	1	3	2	5	5	4	4	6	6	3	11	13	63
Total From Multi-Switch	0	0	0	0	0	0	0	2	0	0	0	2	0	0	5	9
Total Stars	0	5	32	69	100	43	60	71	76	64	51	55	66	89	197	978
Inter-Firm Moves	0	0	0	1	3	2	5	9	4	4	6	10	3	11	25	83
Cohort Movement pct.	*0.0%*	*0.0%*	*0.0%*	*1.4%*	*3.0%*	*4.7%*	*8.3%*	*12.7%*	*5.3%*	*6.3%*	*11.8%*	*18.2%*	*4.5%*	*12.4%*	*12.7%*	*8.5%*

Gunz Canadian Biotech Managers

Time Elapsed	0	1	2	3	4	5	6	Totals
Total Managers	530	256	275	282	163	116	634	2256
Free Moves	0	0	1	4	0	2	7	14
Cohort Movement pct.	*0.0%*	*0.0%*	*0.4%*	*1.4%*	*0.0%*	*1.7%*	*1.1%*	*0.6%*

Angel Semiconductor Engineers

Time Elapsed	0	Totals
Total Engineers	275	275
Free Moves	209	209
Cohort Movement pct.	*76.0%*	*76.0%*

Exhibit 24 - Comparison of Human Capital Movement Statistics for Pharmaceutical Scientists, CBI Managers, and Semiconductor Engineers

Movement Statistics

Moves INTO the Firm (5-year intervals)

Firm	IN (80-84)	IN (85-89)	IN (90-94)	Total (1980-1994)
GLAXO	0	4	8	12
MERCK	1	1	6	8
S-K-B	0	0	6	6
B-M-S	0	0	5	5
ABBOTT	0	3	2	5
SEARLE	0	4	0	4
CIBA-GEIGY	0	1	3	4
UPJOHN	1	0	2	3
B-W	0	0	2	2
HOFFMAN	0	0	2	2
LILLY	0	0	2	2
PFIZER	0	0	2	2
FUJISAWA	1	0	1	2
YAMANOUCHI	0	0	1	1
BRISTOL-MYERS	0	0	0	0
SQUIBB	0	0	0	0
BEECHAM	0	0	0	0
HOECHST	0	0	0	0
SANKYO	0	0	0	0
TAKEDA	0	0	0	0

Exhibit 25 - Movement Statistics - Movements INTO the Firm

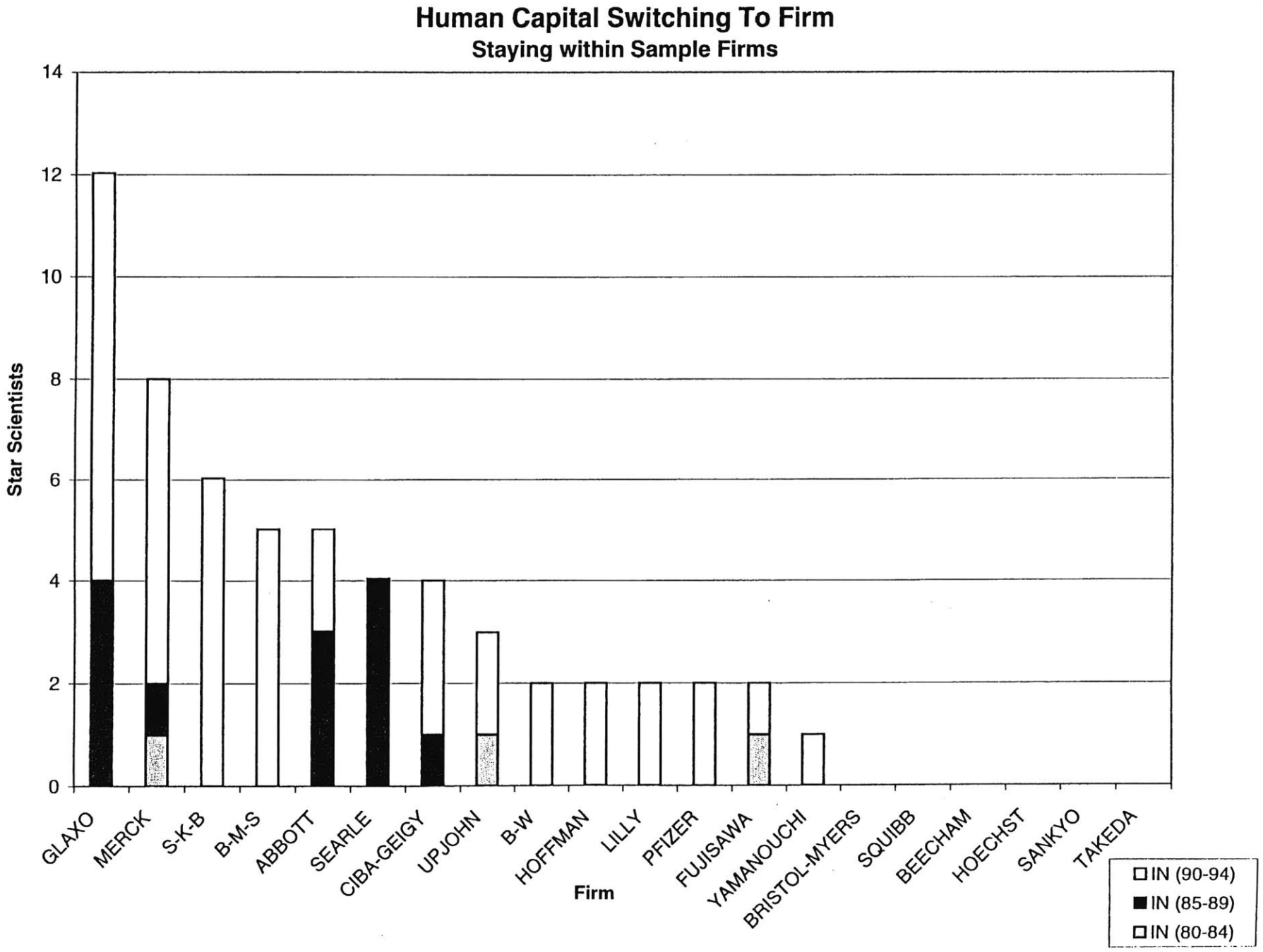


Exhibit 26 - Human Capital Movements INTO the Firm

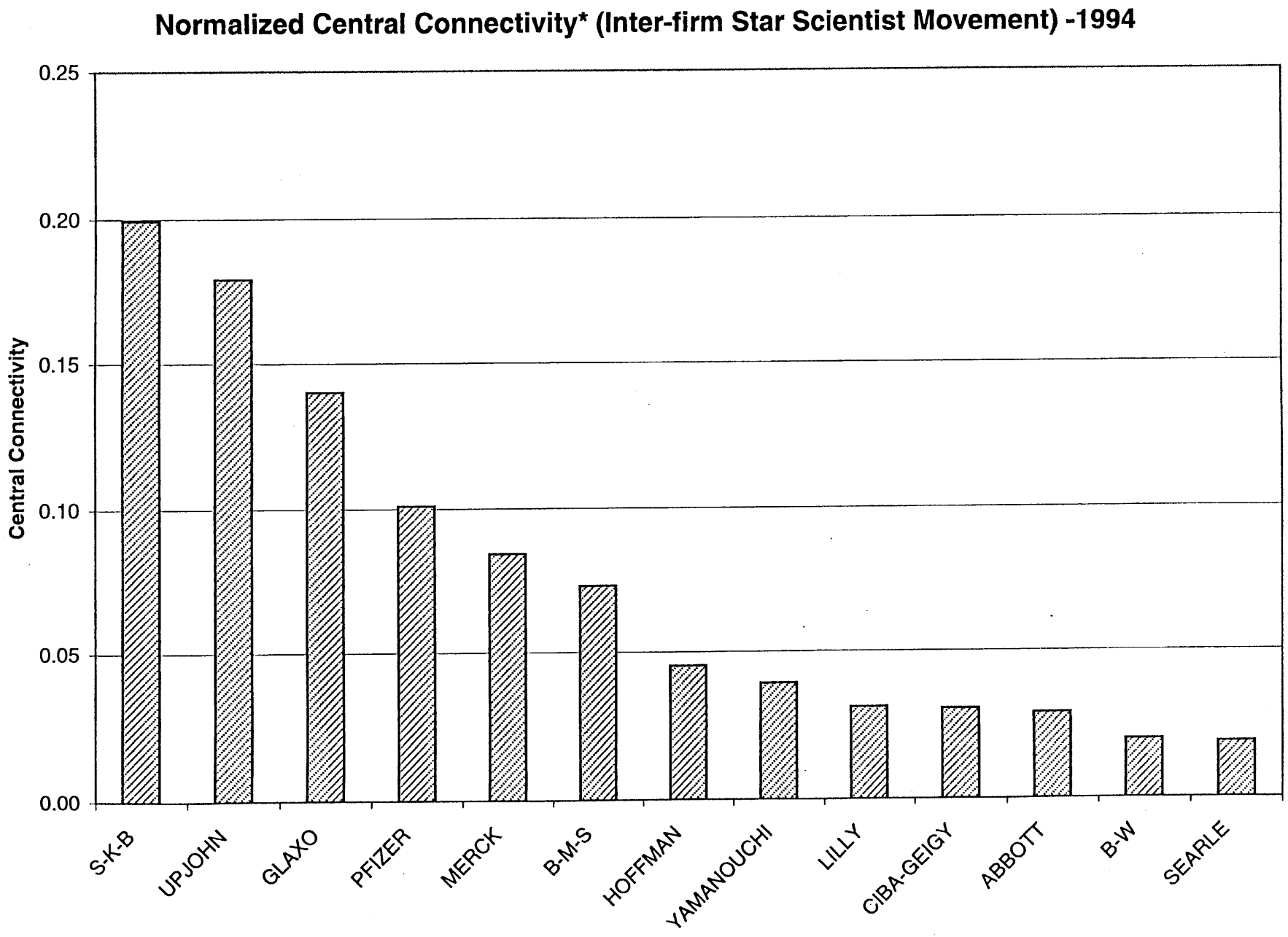


Exhibit 27 - Normalized Measures of Central Connectedness by Firm

Drivers of Research Productivity
(as measured by Important Patent Output)

	Important Patents (t-stats)									
EQUATION	1a	2a	3a	4a	5a	6a	7a	8a	9a	10a
C	54.45 8.59	59.48 11.93	46.50 7.44	53.45 8.70	50.14 7.70	48.18 7.78	-48.07 -1.21	41.24 6.09	39.31 5.83	38.08 5.62
Aucount	-0.05 -2.99	-0.01 -1.39	-0.05 -3.64	-0.04 -3.87	-0.05 -3.73	-0.05 -3.96	-0.02 -1.81	-0.01 -0.84	-0.01 -0.53	0.00 -0.39
Sales	0.00 1.57		8.4E-06 2.88	4.9E-06 1.71	9.5E-06 3.21	8.1E-06 2.79	1.1E-05 3.38	8.6E-06 2.62	1.1E-05 3.18	1.1E-05 3.34
Star1	-0.17 -0.41	-0.05 -0.14	1.02 4.71							
Star2	7.44 2.59	8.34 3.98		7.37 6.10						
Star3	2.03 0.66	-4.74 -2.20			10.31 4.48					
Tot_Star						0.91 5.15				
Adj_Hum_Cap							48.40 2.27			
Movement_A								3.75 0.63		
Movement_B									5.20 1.70	
central										5.81 2.13
R-Squared	0.36	0.23	0.28	0.36	0.36	0.31	0.17	0.13	0.15	0.16
Observations	168	168	106	106	106	168	168	106	106	168

EXHIBIT 28 - ESTIMATION OF IMPORTANT PATENT OUTPUT
Human Capital Movement Models

Drivers of Research Productivity
(as measured by Important Patent Output)

	LOG(Important Patents) (t-stats)									
EQUATION	1b	2b	3b	4b	5b	6b	7b	8b	9b	10b
C	1.51	10.02	-0.72	-0.15	-2.01	-0.60	-3.10	-9.95	-7.78	-11.55
	0.47	7.00	-0.31	-0.05	-0.61	-0.26	-1.30	-1.38	-1.31	-1.93
L_Aucount	-1.10	-0.94	-0.58	-0.76	-0.99	-0.64	-0.52	-1.21	-1.25	-1.40
	-2.60	-3.82	-2.26	-2.55	-2.38	-2.43	-2.84	-1.52	-2.15	-2.44
L_Sales	0.68		0.54	0.59	0.81	0.55	0.60	1.48	1.34	1.67
	2.34		2.54	2.36	2.57	2.59	3.06	1.85	2.16	2.67
L_Star1	-0.68	-0.72	0.14							
	-2.29	-2.85	1.03							
L_Star2	1.07	1.39		0.30						
	3.42	5.10		1.58						
L_Star3	0.27	0.38			0.44					
	1.00	1.67			1.52					
L_Tot_Star						0.17				
						1.29				
L_Adj_Hum_Cap							2.08			
							2.33			
L_Movement_A								-0.17		
								-0.28		
L_Movement_A									-0.04	
									-0.11	
L_central										-0.35
										-0.97
R-Squared	0.44	0.43	0.21	0.07	0.09	0.07	0.09	0.19	0.16	0.17
	161	75	80	51	161	161	161	21	36	161

EXHIBIT 29 - ESTIMATION OF log(IMPORTANT PATENT OUTPUT)
Human Capital Movement Models

APPENDIX B

Exhibits B1-B4

Post Employment

Top Tercile University		Mid Tercile University		Bottom Tercile University	
Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0.10	0.15	0.18	0.26	0.06	0.13

PUBLIC		HOSPITAL		INDUSTRY	
Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0.05	0.11	0.28	0.38	0.32	0.33

NIH	
Mean	Standard Deviation
0.00	0.00

Pre -Employment

Top Tercile University		Mid Tercile University		Bottom Tercile University	
Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0.26	0.19	0.32	0.19	0.07	0.12

PUBLIC		HOSPITAL		INDUSTRY	
Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
0.06	0.18	0.09	0.13	0.01	0.02

NIH	
Mean	Standard Deviation
0.18	0.23

Exhibit B1 - Industry-Wide Pre- and Post-Employment Statistics

Background Statistics - Prior to Joining Firm

Percentages - Before Work								
	U1	U2	U3	PUBLIC	HOSPITAL	INDUSTRY	NIH	Other
ABBOTT	0.65	0.18	0.03	0.03	0.09	0.03	0.00	0.00
B-W	0.00	0.60	0.00	0.00	0.40	0.00	0.00	1.00
MERCK	0.29	0.29	0.15	0.02	0.13	0.04	0.09	7.00
HOFFMAN	0.00	0.40	0.00	0.60	0.00	0.00	0.00	0.00
S-K-B	0.15	0.12	0.00	0.03	0.03	0.00	0.68	2.00
GLAXO	0.25	0.00	0.00	0.00	0.25	0.00	0.50	0.00
LILLY	0.47	0.33	0.13	0.00	0.07	0.00	0.00	1.00
PFIZER	0.20	0.20	0.40	0.00	0.00	0.00	0.20	0.00
UPJOHN	0.42	0.50	0.00	0.00	0.08	0.00	0.00	0.00
CIBA-GEIGY	0.20	0.60	0.00	0.00	0.00	0.00	0.20	1.00
B-M-S	0.27	0.30	0.03	0.03	0.00	0.07	0.27	0.00
TAKEDA	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
SEARLE	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
AVERAGE	0.26	0.32	0.07	0.06	0.09	0.01	0.18	
STDEV	0.19	0.19	0.12	0.18	0.13	0.02	0.23	

Exhibit B2 - Employment Statistics (Prior to Joining Firm)

Movement Statistics - After Leaving Firm

Percentages (AW)								
	U1	U2	U3	PUBLIC	HOSPITAL	INDUSTRY	NIH	Other
ABBOTT	0.40	0.00	0.00	0.00	0.40	0.20	0.00	2
B-W	0.27	0.09	0.00	0.00	0.18	0.45	0.00	4
MERCK	0.17	0.06	0.06	0.17	0.06	0.50	0.00	1
HOFFMAN	0.31	0.00	0.31	0.08	0.00	0.31	0.00	2
LILLY	0.00	0.67	0.33	0.00	0.00	0.00	0.00	0
PFIZER	0.00	0.33	0.00	0.00	0.33	0.33	0.00	0
UPJOHN	0.00	0.14	0.00	0.00	0.14	0.71	0.00	2
BRISTOL-MYERS	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0
GLAXO	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0
FUJISAWA	0.00	0.67	0.00	0.33	0.00	0.00	0.00	1
HOECHST	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0
SANKYO	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0
CIBA-GEIGY	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0
AVERAGE	0.10	0.18	0.06	0.05	0.28	0.32	0.00	1.09
STDEV	0.15	0.26	0.13	0.11	0.38	0.33	0.00	

Exhibit B3 - Employment Statistics (Prior to Joining Firm)

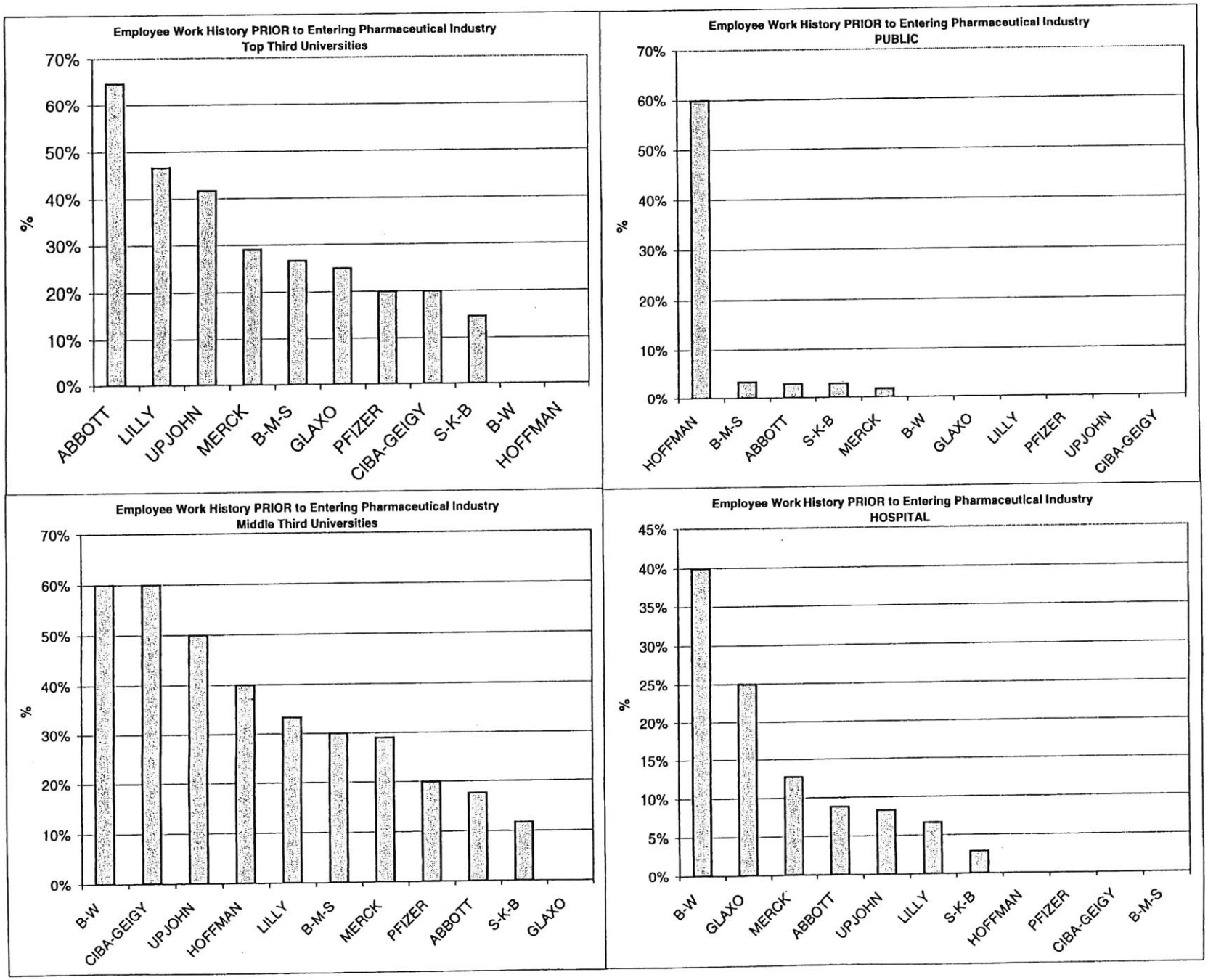
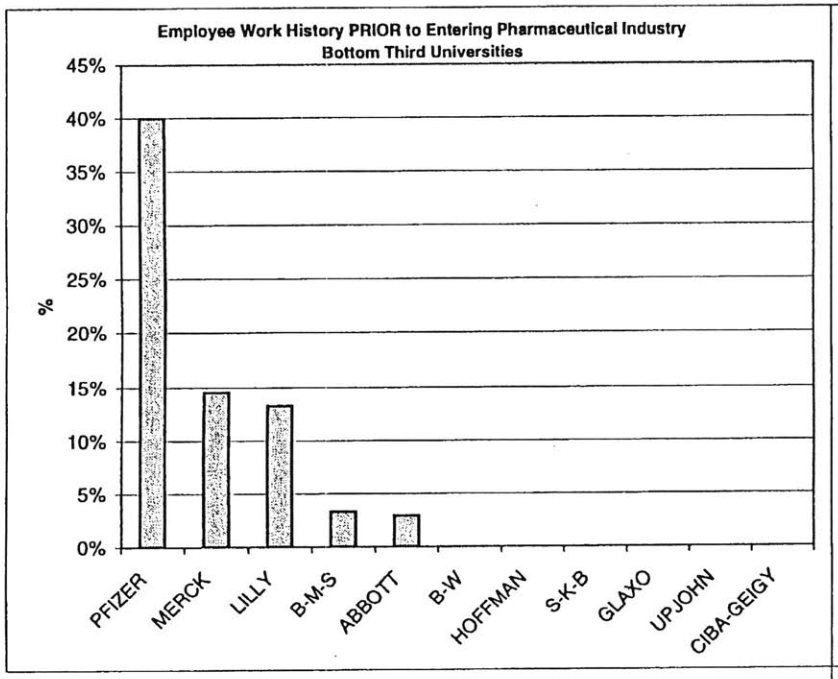
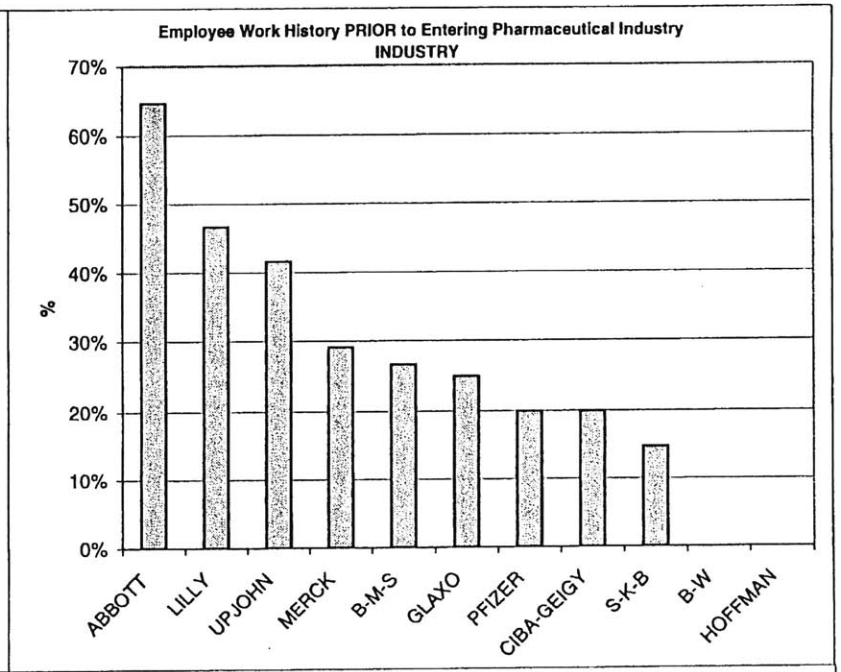


Exhibit B4 - Graphical Firm-level Background Data





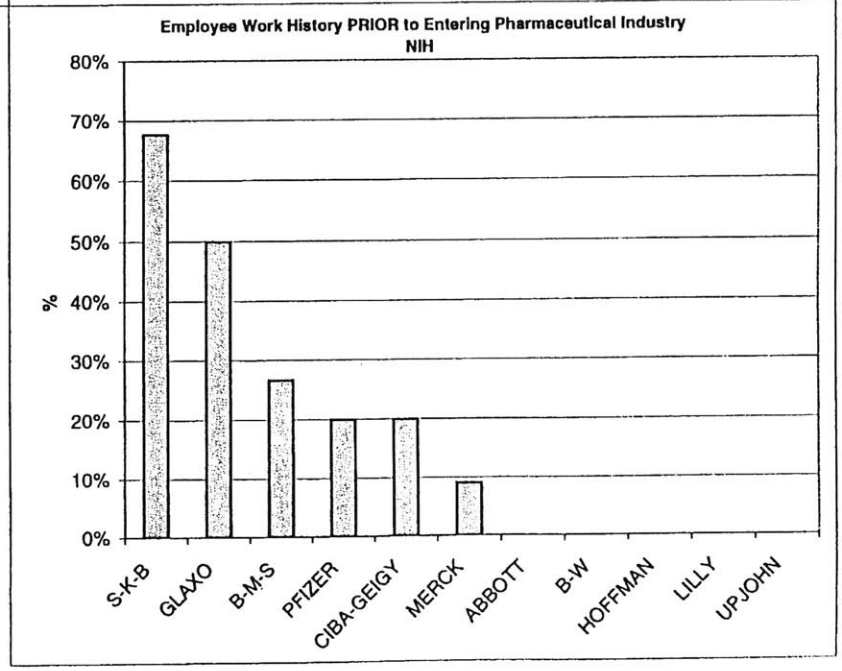


Exhibit B4 - Graphical Firm-level Background Data